Making a case for the use of digital footprint data for evidence-based policies in response to human mobility changes after COVID-19 in Latin America

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Abstract. Text for abstract

1 Introduction

Digital footprint data (DFD) are increasingly becoming a vital component of the data ecosystem to measure and monitor human mobility. DFD are digital traces left as a result of social interactions on digital platforms, such as the Internet through web search engines (e.g. Google), social media networks (e.g. Twitter and Facebook), commercial systems in the way of transactions (e.g. payment systems), sensor networks to capture environmental and human changes (e.g. fitness trackers, temperature and sound sensors), and imagery collected via satellites, cameras, drones, CCTV and imaging devices. Digital traces encoding location recorded through Call Detail Records (CDRs), eXtended Detail Records (XDR), Global Positioning System (GPS), Bluetooth and smart card data have been particularly valuable to reconstruct a traceable digital representation of human mobility.

These forms of DFD offer three key opportunities to capture human mobility (1) at higher geographical and temporal granularity; (2) over extensive geographical coverage comprising entire population systems or geographical areas; and (3) in real or near-real time [REF]. These attributes have enabled to complement traditional data sources to capture human mobility at various geographically scales, including urban mobility [REF], internal migration [REF] and international migration [REF]

Yet, the use of DFD poses significant challenges. These data are a by-product of administrative processes. They are not collected for research purposes. Their use involves major conceptual, methodological, data and ethical challenges [REF]. For instance, turning raw DFD into actionable, usable information requires significant data engineering, embracing data-driven hypotheses, accounting for data biases, ensuring privacy and anonymity, and integrating and validating the resulting outcomes with external data sources [REF]. These challenges to be overcome to unleash the opportunities offered by DFD.

An increasing number of “Data for Good” initiatives have been developed to leverage the potential positive social impact of DFD. These include data governance, data strategy and data sharing initiatives

(European Commission. Joint Research Centre. 2022). Data governance initiatives involve efforts focused on the provision of guidance about best practices for the collection, storage, share and use DFD for the social good. Data strategy initiatives focus on building capacity in civil society by designing data strategies for nonprofits and government agencies, such as Data-Pop Alliance and the Open Data Institute. Data sharing initiatives entail the creation and facilitation of access to datasets by data providers for organisations seeking to generate data solutions and positive social impact. These initiatives include Data for Good at Meta and Waze Partner Hub.

Enabled by these initiatives, the use of DFD seems to have been - much more promising in less developed countries given data scarcity.

- Discuss how digital footprint data have been used in more developed countries or global north
- Highlight the limited use of digital footprint data in the global south
- Aim: Use of digital footprint data for mobility and policy response
- Argue case for COVID and mobility
- Structure

2 Background

2.1 The impact of COVID-19 on internal population movements

Globally, there is evidence that the COVID-19 pandemic constrained both shorth- and long-distance movements within national boundaries (Nouvellet et al. 2021; González-Leonardo, Rowe, and Fresolone-Caparrós 2022; Wang et al. 2022; Rowe, González-Leonardo, and Champion 2023). Declines were documented across the Global North during the first year of the pandemic, in the United States (Ramani and Bloom 2021), some European countries, Japan and Australia (Rowe, González-Leonardo, and Champion 2023), from 2.5% in Spain to 8.5% in Australia. Drops mostly occurred when governments implemented non-pharmaceutical interventions, such as stay-at-home requirements, travel restrictions, mobility restrictions, business and school closures. Levels of human mobility within countries, however, recovered pre-pandemic values following the elimination of lockdowns and other stringency measures. Declines on human mobility were attributed to lockdowns, increasing teleworking and restrictions of movements, but also to a loss of labour market dynamism as a consequence of the economic recession during the pandemic (Perales and Bernard 2022). In addition to evidence in the Global North, drops in internal population movements were also found in Latin American, declining by about 10% during periods of severe stringency measures (Aromí et al. 2023). The highest declines occurred in Bolivia, Ecuador and Argentina, ranging from 16% to 19%, while they did not reach 3% in Paraguay and Venezuela.

In global north countries, the COVID-19 pandemic also modified the patters of internal population movements between large cities and areas with lower population densities (Rowe, González-Leonardo, and Champion 2023). Variations were found in the United States (Ramani and Bloom 2021), United Kingdom (Rowe, González-Leonardo, and Champion 2023; Wang et al. 2022), Spain (González-Leonardo et al. 2022; González-Leonardo, Rowe, and Fresolone-Caparrós 2022), Germany (Stawarz et al. 2022), Sweden (Vogiazides and Kawalerowicz 2022), Norway (Tønnessen 2021), Australia (Perales and Bernard 2022) and Japan Kotsubo and Nakaya (2022). Net-migration rates in large cities declined in the United States, Germany, Norway, Sweden and Japan during 2020, while they increased in their suburbs. (Ramani and Bloom 2021) called this phenomenon as "donut effect", reflecting a decrease in population inflows to urban centers (urbanization) and a growth of movements from cities to their suburban rings (suburbanization). Nonetheless, there is no evidence of a "donut effect" in the United Kingdom, Spain and Japan, as net-flows in suburbs did not show significant changes. However, inflows to large cities also declined and counterurbanisation movements increased, reflecting unusual population gains in rural areas. In Spain, Sweden, Japan and Germany, holiday town with second homes of wealthy individuals were also found as popular destination for people leaving large cities during the pandemic. It suggests that wealthy populations and professionals who are able to work remotely seems to underpin movements from large cities to areas with lower population densities where they own second residences (Haslag and Weagley 2021; Tønnessen 2021).

Despite the above-mentioned changes to the human mobility system during the pandemic, research suggests that pre-existing macro-structures of internal population movement across the rural-urban continuum were not altered, since the majority of movements continued to occur within and between urban areas, and changes are not likely to endure (Rowe, González-Leonardo, and Champion 2023). For instance, mobility patterns returned to those registered before the pandemic after the lockdown in the United Kingdom (Rowe et al. 2022; Wang et al. 2022). The pandemic caused minor impacts on spatial patterns of internal population movements in Australia, and variations attributed to COVID-19 disappeared in late 2020 (Perales and Bernard 2022). Urbanisation levels returned to those register prior to the pandemic in Spain when the lockdown ended in mid-2020 (González-Leonardo et al. 2022), although unusually high levels of counterurbanisation persisted over 2021, despite decreasing over the year (González-Leonardo, Rowe, and Fresolone-Caparrós 2022).

Previous work provided a good understanding on how human mobility across the rural-urban hierarchy was affected by the pandemic in the Global North. However, less is known about COVID-19 impacts on movements between cities, suburbs and rural areas in the Global South and the durability of potential changes. Anecdotal evidence, based on small surveys carried out in India (Irudaya Rajan, Sivakumar, and Srinivasan 2020) and South Africa (Ginsburg et al. 2022), pointed out that flows from large cities to less populated areas increased due to the return of workers to their hometown, while movements of labour force to cities decreased. Both surveys saw that the economic downturn caused by non-pharmaceutical interventions during the pandemic (Ghosh, Seth, and Tiwary 2020) underpinned declining inflows of workers to cities and increasing returns among people who lost their jobs. The above-mentioned anecdotal evidence suggests that vulnerable populations seem to have played a role in movements to and away from large cities during the pandemic in the Global South.

Nonetheless, a recent study demonstrated that wealthy individuals from large cities in Brazil, Colombia, Indonesia, Mexico, Philippines and South Africa moved to lees populated areas during the first wave of COVID-19 (Lucchini et al. 2023). On average, residents from high-wealthy neighborhoods were 1.5 times more likely to leave cities compared to those from low-wealthy areas. These finding is in line to results in Global North countries. Despite anecdotal evidence suggesting pandemic impacts on the patterns of internal population movements across the rural-urban hierarchy in some Global South countries, lack of data has not allowed for quantifying the magnitude and durability of potential impacts on the human mobility system. To fill the gap, we use Facebook data to analyse the effect of COVID-19 on the patterns of internal population movements in Argentina, Chile, Colombia and Mexico.

2.2 Human mobility across the rural-urban continuum in Latin American countries

Currently, Latin America has the highest urbanization rate in the world after North America, totaling 81% (Nations" 2019). It means that the population is highly concentrated across space within Latin American countries, particularly in large cities with more than one million inhabitants, where half of urban residents are settled (Pinto da Cunha 2002; A. E. Lattes, Rodríguez, and Villa 2017). High urbanization rates are due to massive levels of population redistribution from rural settlements to cities until the 1980s, mostly during the fast industrialisation period from early-1950s to late-1970s, when population gains were mainly observed in chief cities (Firebaugh 1979; A. Lattes 1995; J. Sobrino 2012). Internal population movements in Latin America have been declining since the 1980s, as rural population stocks were depleted (Chávez Galindo et al. 2016) and the industrial crisis leaded to deconcentration trends in large cities, such as Santiago de Chile [González Ollino and Rodríguez Vignoli (2006)) or Mexico City (Jaime Sobrino 2006), where long distance inflows have declined. In sum, middle size cities became more attractive to internal migrants as a consequence of increasing domestic and foreign investment in export-oriented industries or tourism activities, leading to geographic economic dispersal (Brea 2003; Pérez-Campuzano 2013; Chávez Galindo et al. 2016). Nowadays, movements between cities dominate the internal migratory system in Latin American countries (Bernard et al. 2017; Rodríguez-Vignoli and Rowe 2018; Nations" 2019). About 80% of internal migrants moved between cities, according to the 2010-11 census round (Rodríguez-Vignoli and Rowe 2018). Medium-sizes cities from 500.000 to 1 million residents showed the highest population gains by internal migration, while large cities with more than 1 million residents registered balanced rates and small cities with less than 500.000 inhabitants lost population by internal mobility (Rodríguez-Vignoli and Rowe 2018).

Latin American cities have shown a significant growth in terms of land development in their urban peripheries. Since the 1970s, large cities, such as Santiago de Chile, Buenos Aires or Mexico City, but also middle and small cities have experienced suburbanisation (Graizbord and Acuña 2007; Chávez Galindo et al. 2016). Suburbanisation flows comprise middle- and high-class families moving from cities to auto-segregated areas in the periphery (Borsdorf 2003; Rodríguez Vignoli and Rowe 2017). Low-income individuals also settle in slams across suburbs but, in this case, in those areas where the land cost is cheaper (Janoschka 2002; Rodríguez Vignoli and Rowe 2017). Both residents in auto-segregated areas and slams commute daily to cities, mainly for work reasons (Chávez Galindo et al. 2016). Most recently, reurbanisation trends have been identified in central areas due to gentrification dynamics, although suburbanization flows continue to dominate short distance movements (J. Sobrino 2012; Chávez Galindo et al. 2016). In this repot, we explore COVID-19 impacts on the patterns of human mobility across the rural-urban continuum in Latin America.

3 Data

3.1 Meta-Facebook Data

The multinational technology conglomerate Meta offers a range of data products aimed for social good through their Data for Good programme, which is open to trusted partners including universities, non-profit organisations, and international institutions. The data is available at small spatial and temporal scales and has the potential to improve how we respond to real-world crises or unusual events, such as earthquakes, hurricanes, floods or pandemics (Maas et al. 2019). In particular, the Data for Good programme offers location data, gathered from Facebook app users who have the Location Services setting turned on on their smartphone. Meta uses the location data for a wide variety of applications in addition to the Data for Good programme, including providing customised services to its users such as finding nearby friends, providing information about nearby Wi-Fi hotspots, and location-relevant ads. The collected location data also enables targeting of AMBER alerts and prompts to check-in as "safe" after a hazard event.

While the raw location data remains available only to the data owners, the datasets available through Data for Good consist of anonymised and aggregated near real-time data corresponding to a period of crisis which might extend over several weeks, months or years. The datasets also contain historical location data as a baseline period before the event (Maas et al. 2019).

3.2 Facebook data

In this report, we analyse human mobility during the COVID-19 pandemic using the datasets Coronavirus Disease Prevention Map of Facebook Population During Crisis (Tile Level) and Coronavirus Disease Prevention Map of Facebook Movements During Crisis (Tile Level), hereinafter Facebook Population and Facebook Movements datasets. Specifically, we analyse human movement data from four Latin American countries: Argentina, Chile, Colombia and Mexico. The former dataset allows us to analyse how the number of Facebook users changed across space during the COVID-19 pandemic. The focus of our analysis, however, is on the latter, which contains information about the evolution of spatial patterns of mobility during COVID-19.

The datasets contain data corresponding to a two-year period, starting on the 10th March 2020 and ending in mid-March 2022. Data are temporally aggregated into three 8-hour daily time windows (00:00-08:00, 08:00-16:00 and 16:00-00:00). The datasets also include data for baseline levels before COVID-19 based on a 45-day period ending on the 10th of March of 2020. The baseline data is computed using an average for the same time of the day and day of the week in the period preceding the crisis (e.g., average over all data collected on a Monday from 00:00 to 8:00 or average over all data collected on a Wednesday from 16:00 to 00:00). For more details on how the baseline values are computed, see (Maas et al. 2019).

The data is spatially aggregated into units called Tiles, according to the Bing Maps Tile System developed by Microsoft (Microsoft). This widely-used system offers a variety of world partitions, where the spatial units are square cells at various levels of resolution. The Data for Good datasets are typically generated using Bing tile levels 13 through 16, where level 13 results in tiles that are about 4.9 x 4.9 km at the Equator (Maas et al. 2019).

The Facebook Population data provides the number of mobile app users who have the Location Services setting turned on, aggregated by tile. The location of each user in a given 8-hour time window is determined by the tile where they spent most of the time within that window. The Facebook Movement data captures the number of mobile app users who have the the Location Services setting turned on moving between a pairs of tile. The origin and destination of a movement are defined as the locations where a user spent most time between two subsequent time windows (e.g., 00:00-8:00 and 8:00-16:00). In addition to the count data, both the Facebook Population and the Facebook Movement datasets include the percentage difference between the number of counts during the crisis period and the corresponding baseline level for each entry.

Prior to releasing the datasets, information on personal characteristics of users is removed and several techniques are applied to ensure privacy and anonymity. Small-count dropping is one of these techniques, whereby a data entry is removed from the data set if population or movement counts are lower than 10 during the crisis period, the baseline period or both. While this technique makes it harder to identify individual users based on their movement patterns, the removal of data entries containing locations with small counts may lead to an underrepresentation of the population in these places. Another of these techniques 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. In order to produce a smooth population count surface, spatial smoothing using inverse distance-weighted averaging is also applied (see (Maas et al. 2019) for details).

3.3 COVID-19 stringency data

To understand the patterns of mobility in the context of the COVID-19 pandemic, we use the stringency index as a measure of the level of nonpharmaceutical interventions to COVID-19, such as social distancing and lockdowns. The stringency index ranges from 0 to 100, with 100 being the value corresponding to the most strict scenario. The values for the stringency index were retrieved from the COVID-19 government response tracker (https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker). For more information, see Hale et al. (Hale et al. 2021).

3.4 Worldpop population data

An additional data set from WorldPop was used to capture the spatial distribution of actual population in the different countries analysed here. The WorlPop poulation dataset is in raster format and contains gridded population data at 1 sqkm resolution. We processed the WorlPop population data so it is spatially aggregated according to the Bing Maps Tile System. The level of detail was chosen so it coincides with that used in the Facebook Population and the Facebook Movements data for each of the countries analysed in this study.

4 Methods

4.1 Classifying Bing tiles according to their population density

In this study, we aim to understand how the population density at the origin and destination locations might influence mobility behaviours. To help characterise the population density of different locations, we consider the Worldpop population data aggregated into Bing tiles. We then use the Jenks natural breaks classification method in order to obtain 10 categories of population density, with categories 1 and 10 being the least and most dense categories respectively. This categorisation of Bing tiles, which offers a greater level of detail than the traditional binary rural/urban classification, is represented in Figure 1. In the Figure, we have included maps for the four countries in the study showing the Bing tiles coloured according to the population density category they belong to. It is possible to see from the inset histograms that Argentina and Chile have very skewed distributions due to the strong concentration of highest-density areas in just a few tiles belonging to their capital cities, Buenos Aires and Santiago. By contrast, Colombia and Mexico display more balanced population density distributions across tiles.

It is important to note that the cut-off values for each population density category vary across countries, but we expect tiles belonging to the same category in each country to have similar functions in the urban hierarchy (e.g. the high-density tiles belonging to category 10 always correspond to major urban centres that act as socioeconomic hubs in their respective regions).

In order to provide a better intuition of the type of areas that each population density category represents, we also include (**tab-places?**), where we give a few examples of names of places belonging to each density category.

[Table]{#tab-places}

4.2 Tile-based mobility metrics

We measured changes in the intensity of movement by computing the variation in the number of inflows and outflows by population density category, i.e. the number of people entering and leaving tiles belonging to a specific population density category. We did this across all tiles of Argentina, Chile, Colombia and Mexico for two distinctive months during the course of the COVID-19 pandemic: May 2020 and March 2022. Specifically, we use the percentage change in the intensity of a population flow as provided in the Facebook Movement data sets (Maas et al. 2019). For each entry in the dataset, which represents a flow of people between an origin and a destination tile, the percentage change in the intensity of the flow is computed as:

$$Change(\%) = (\frac{n_{crisis}}{n_{baseline}} - 1) \times 100$$

where n_{crisis} corresponds to the number of people moving and $n_{baseline}$ corresponds to the number of people that would be expected to move in the baseline pre-pandemic period at the same time of the day, on the same day of the week and between the same origin and destination tiles. A positive value indicates an increase in the extent of population movement relative to the baseline levels. A negative score represents a decrease, while a zero score denotes no changes.

We then group the population flows according to the population density category of origin (for outflows) or destination (for inflows) during the two selected months. We generate boxplots for the percentage change variable, corresponding to each population density category. The boxplots illustrate the spread of values of percentage change in the number of inflows and outflows during a selected month for each population density category.

Furthermore, we also considered the impact of the pandemic in the mobility patterns by analysing changes in net mobility. We looked at the evolution of netflows, i.e. the difference in the number of people entering and leaving a location, throughout the whole period of the dataset. The netflows where computed as

$$netflows = inflows - outflows$$

where in this case, $inflows$ and $outflows$ represent the total number of people entering and exiting a given density category in a given month. Therefore, we can obtain the netflows corresponding, for example, to August 2021 for population density category 8 or to October 2020 for population density category 3.

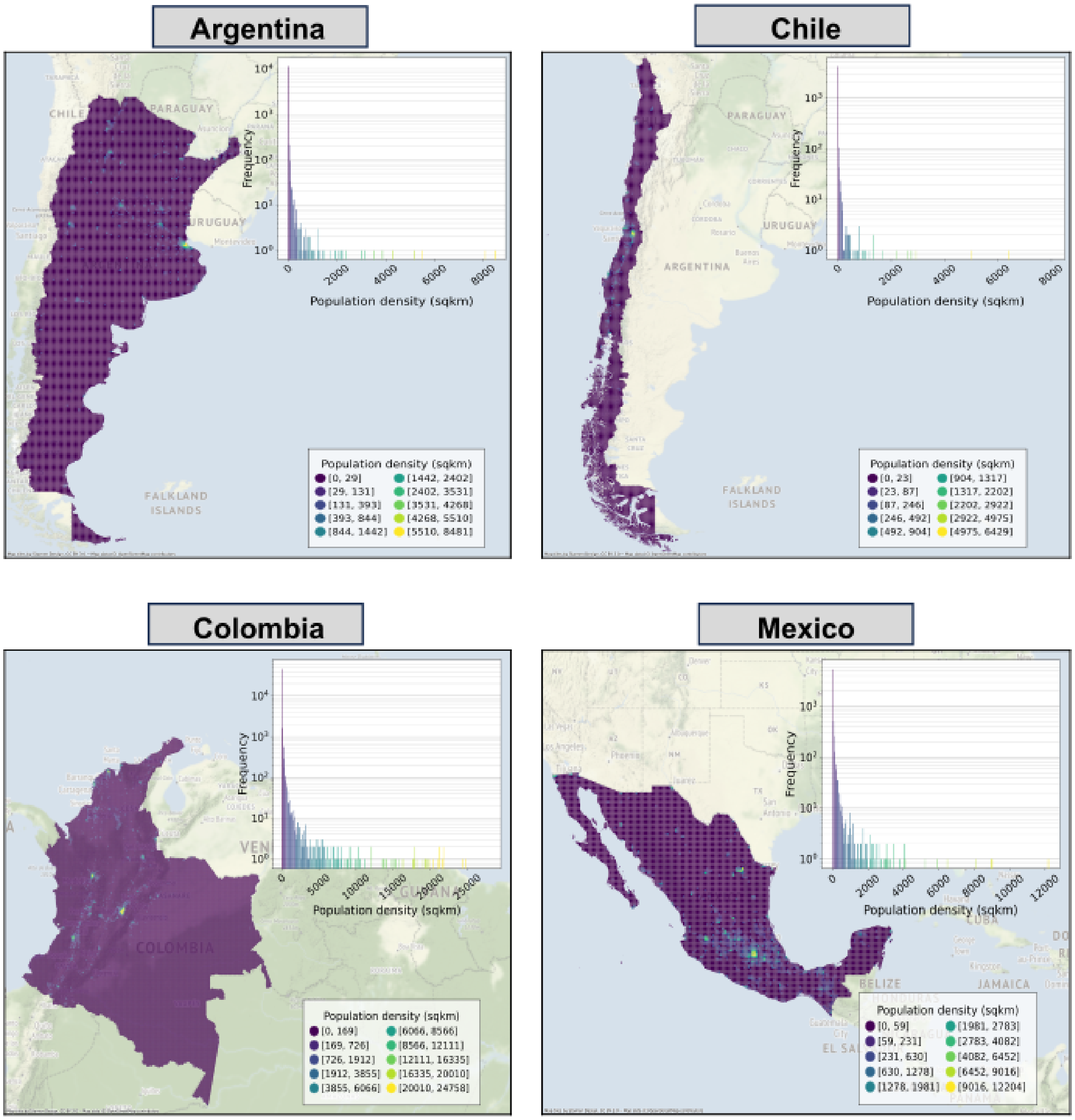

Figure 1: Maps showing the density classes for the different tiles in Argentina, Chile, Colombia and Mexico.

4.3 Local vs long-distance mobility

All the tile-based metrics described above were computed for population flows where the Euclidean distance between the origin and the destination location was greater than 0 km. Population flows for which the recorded distance was 0 km were discarded. We also split the Facebook Movement dataset into two, one considering flows where the straight line distance covered by the movement was below 100 km and the other for flows covering 100 km or more. The rationale for this stratification is that we expect the COVID-19 pandemic to affect mobility differently at different spatial scales. As highlighted in the background section, a decrease in inflows to the urban core coupled with an increase in inflows in suburban was observed in multiple large cities from the Global North, indicating a change in the commuting patterns. Population flows from big cities to rural areas were also observed in some GLobal North countries, which suggests a change in internal migration patterns in the form of an urban exodus. Given that the information contained in the Facebook Movement data set is aggregated, we are unable to infer the purpose of a movement, but separate analysis of population flows that cover under and over 100 km separately can help us understand whether the patterns observed in Latin American countries follow the same trends observed in the Global North. In particular, we expect populations flows covering under 100 km to capture local travel such as commutes or day trips, and flows over 100 km to capture longer-distance multi-day trips or even internal migration.

5 Results

5.1 Changes in mobility in May 2020 and in March 2022

We analysed changes in the intensity of inflows and outflows for different population density categories across Argentina, Chile, Colombia and Mexico in May 2020 and March 2022. These two months represent two pivotal points in the pandemic. March provides a good representation of the early days when a series of strong stringency measures were enacted following the WHO's declaration of COVID-19 on the 11th of March 2020 as a global pandemic. March 2022 captures the later days of the COVID-19 pandemic about six months after most of the COVID-19 restrictions had been relaxed in the countries in our analysis.

Figure 2 and Figure 3 show boxplots of the distribution of the percentage change in the number of outflows by areas according to their population density for under and over 100 km, respectively. The boxplots report movements that emerge from each population density category during May 2020 and March 2022. The baseline levels are represented by the dotted line at $y = 0$. Positive values indicate increases in mobility relative to the pre-pandemic period, while negative values indicate a reduction in mobility.

Overall, we observe a consistent decline in outflows across all population density categories for movements under and over 100 km. The decline is specially strong in the early days of the pandemic. We observe some degree of recovery in March 2022, evidenced by the fact that the boxplots appear closer to the baseline levels. Furthermore, we observe a consistent trend whereby the decline in outflows becomes greater as the population density increases, so the largest drops occurred in the most densely populated areas, such as Buenos Aires, Santiago, Bogotá and Mexico City. This effect is specially evident in May 2020, where population flows with destination in tiles belonging to the highest-density category, dropped by more than 50% in some cases. Low-density areas reported lower declines which is some cases are statistically indistinguisahble from 0%.

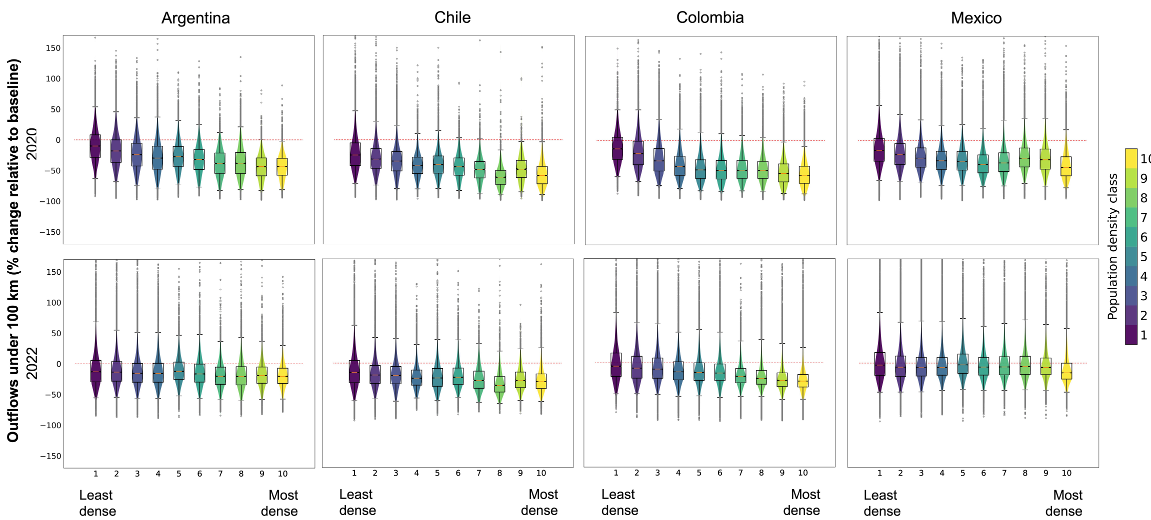

Figure 2: Changes in mobility flows during May 2020 and March 2022 by population density deciles, relative to baseline period. Movements under 100km.

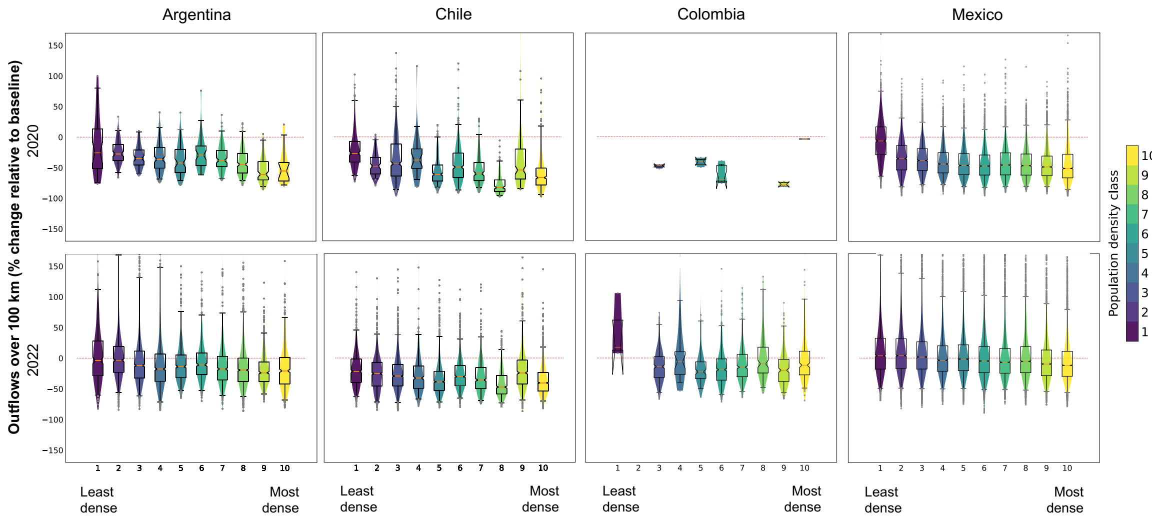

Figure 3: Changes in mobility flows during May 2020 and March 2022 by population density deciles, relative to baseline period. Movements over 100km.

Generally speaking, we also identify a relatively higher level of variability in the percentage change values for low-density categories, showing that the behaviours in these regions might be more heterogeneous than in densely-populated areas.

There are some exceptions to the general behaviours discussed above. Firstly, declines in short-distance movements from high and medium densely areas are slightly lower in Argentina and Mexico than in Chile and Colombia. Second, while outflows over 100 km in Argentina, Chile and Colombia decline more for higher density categories, this trend displays more variability than in the case of Mexico and in the case of ouflows under 100 km. This could be attributed to the smaller sample size of population flows covering more than 100 km.

This last remark leads us to address the issue that in Colombia, both in May 2020 and in March 2022, there are some population density categories with no outflows over 100 km. On the one hand, the tiles used in the Facebook Movements data set to spatially aggregate the data are smaller for the case of Colombia, so fewer movements are recorded per cell. On the other hand, according to Facebook's documentation, three procedures are applied to maintain data privacy, which could be the reason why we have so few population flows covering a distance of more than 100 km recorded in the raw Facebook Movement data set (before aggregating them by month). Of these three procedures, 'small-count dropping' could be specially relevant since population flows with small counts for either the pandemic or the baseline period, are fully removed from the data set. Essentially, in the first place, we have few movements emerging from each tile for each 8-hour time interval due to the small tile size, so when the small count dropping mechanism is applied for each time interval, these low counts are removed from the data set. Therefore, when we aggregate the population flows over a month to generate Figure 2 and Figure 3, some classes of population density end up with no counts at all. Even for density classes containing some counts, the numbers are low, making the results for long-distance movements in Colombia inconclusive. When considering larger tiles, as in Argentina, Chile or Mexico, this effect could be non-existent since the counts are higher, and there are not as many rows in the database to discard due to the small-count dropping procedure.

As we mentioned above, we observe some degree of recovery in March 2022 following the relaxation of COVID-19 restrictions. We observe increases in both short- and long-distance outflows across the population density categories, so that in most cases, the intensity of outflows bounced back closer to pre-pandemic levels. However, not all population density categories recovered to the same extent. Remarkably, while low density areas are fully or almost fully back to pre-pandemic levels, the highest density areas continued to record slightly lower levels of outflows than in the baseline period. This suggests that since the outbreak of COVID-19 there has been less people travelling out of highly-dense areas including the urban core of the capital cities of each country. When looking at the Figures for analogous inflows, which can be found in the Appendix, the same pattern can be observed, suggesting that highly dense areas have seen a consistent reduction in the number of people travelling in and out.

It is worth noting that among all countries, Mexico is the one demonstrating the most significant degree of recovery. Variations across countries could be driven by the different strength and durability of stringency measures. These measures were weaker and implemented for a shorter period of time in Mexico. It is also worth noting that the baseline measurements included in the Facebook Movements dataset were collected from February to mid-March, coinciding with the holiday season in Chile. As a result, mobility patterns during this baseline period might differ from those observed for the remainder of the year.

In summary, based on Figure 2 and Figure 3, we see less people leaving densely-populated areas which suggests that a phenomenon of urban exodus did not take place in the four Latin American countries during the first wave of COVID-19. We observe, however, a general decline in the intensity of population flows from and to all population density categories during early stages of the pandemic, especially for highly-dense areas. This decline shows signs of being temporary, since the number of people moving has almost recovered to pre-pandemic levels as of March 2022.

5.2 Spatio-temporal patterns of population redistribution during COVID-19

We also analysed the spatial impact of mobility on redistributing population across the country during the COVID-19 pandemic. Specifically, we examined the evolution of changes in the net balance between mobility inflows and outflows across the rural-urban hierarchy during the pandemic. We calculated the monthly net movement balance as the difference between mobility inflows minus outflows for individual population density classes during March 2020 to May 2022. Figure 4 and Figure 5 shows the changes in net balance for movements under 100km and over 100km, respectively.

Figure 4 reveals a persistent pattern of fluctuating negative net balances of movements under 100km in the highest population density areas in Argentina, Colombia and Mexico for most of March 2020 to May 2022. The extent of these balances become more notably pronounced after July 2020, but they vary widely by country. Mexico displays the largest negative balances, probably reflecting the fact that it is the most sizable of the countries in our sample. The trend of negative balances indicates that the highest population density areas in Argentina, Colombia and Mexico tended to record a larger number of outward movements than inward movements over distances of less than 100km. As indicated in **?@sec-methods1**, these locations comprise highly dense metropolitan cores predominantly in capital

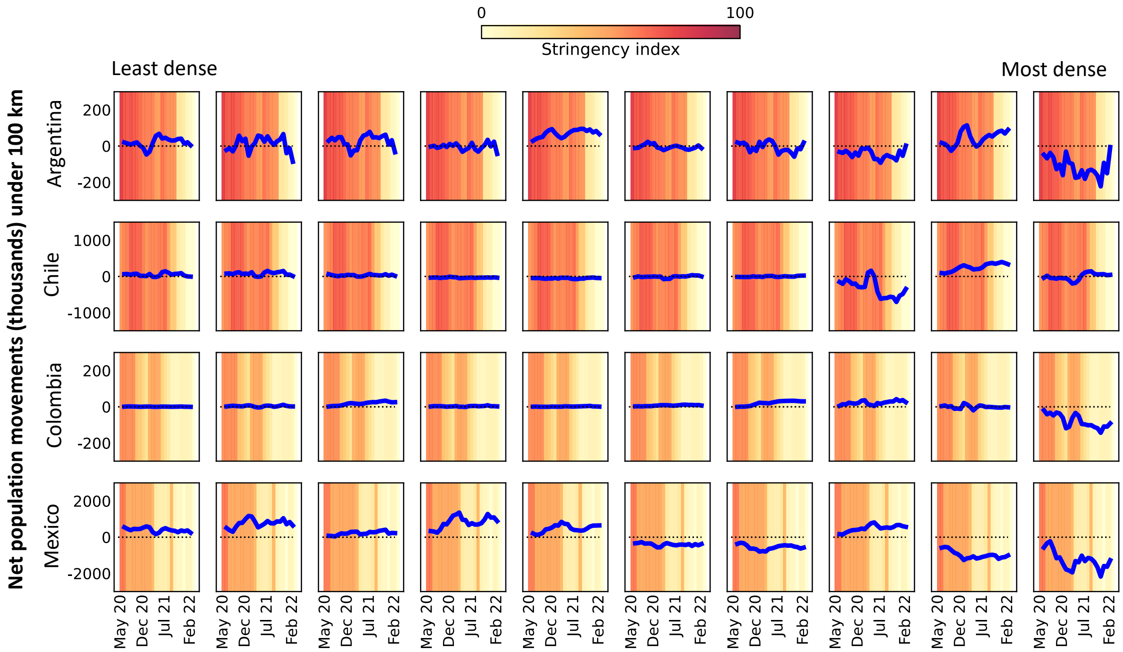

Figure 4: Total number of net movement by population density class over time. Movements under 100km.

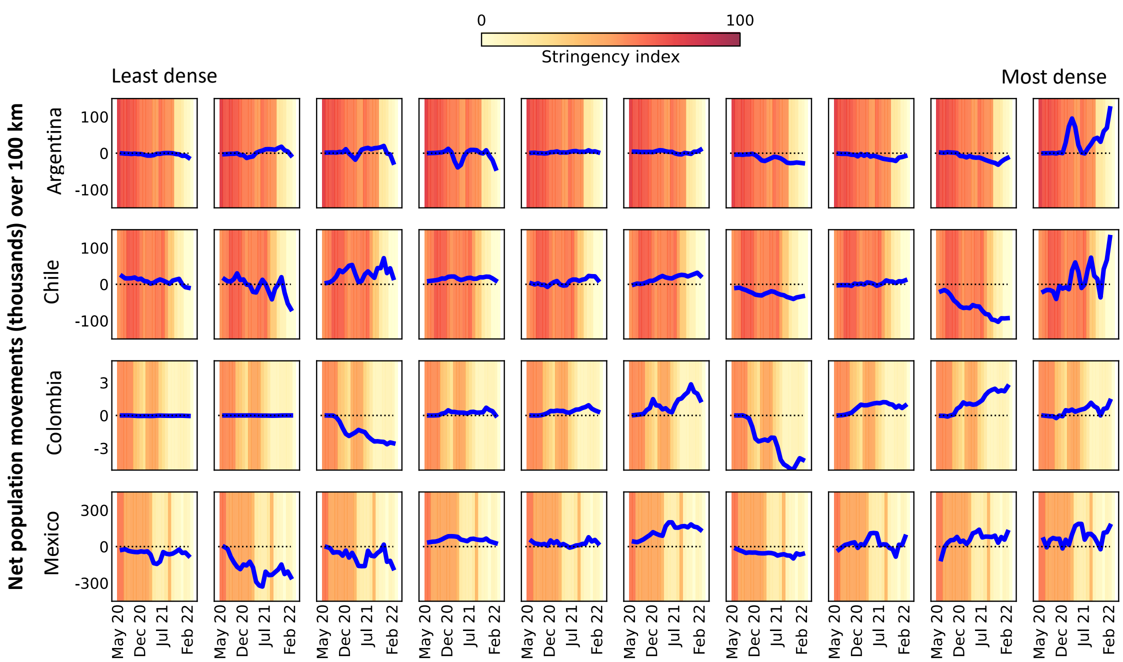

Figure 5: Total number of net movement by population density class over time. Movements under 100km.

cities, including the Central Business District. In Mexico, large negative net balances also occurred in areas of class 9. These areas are particularly in . The spatial concentration of negative net balances in high density areas mirrors the pattern of population loss identified in metropolitan areas in developed countries during the COVID-19 pandemic (Rowe, González-Leonardo, and Champion 2023).

At the same time, Figure 4 shows a relatively consistent positive net balance of movements in specific types of areas along the rural-urban hierarchy. Argentina records a consistent pattern of greater inward movement than outward movement in medium density areas of class 5 type, including , and a trend of irregular net positive balances in the least dense areas of class 1-3 and high density locations of class 9. Areas of class 1-3 in Argentina correspond to rural and sparsely populated regions across the country, while class 9 areas predominantly represent suburban metropolitan and large city areas . In Colombia, positive net balances are less pronounced. They tended to occur in areas of class 3, 7 and 8 over 2021 and 2022, predominantly in . In Mexico, a pattern of consistently positive net balance of movements occurred in the range of less dense areas of class 1 to 5, particularly in

Chile displays a different pattern.

Concerning short-distance movements, those under 100 Km, we do not identify remarkable positive or negative balances during the very first months of the pandemic. However, we do observe a negative net balance in the largest cities of Argentina, Colombia and Mexico during the following months of the pandemic when levels of restrictions were relaxed. This finding may suggest a slight trend of urban exodus and a potential donut effect, with people moving away from core cities of metropolitan regions. This pattern coincides with positive balances across different categories in the urban hierarchy. For instance, the categories of population density 5 and 9 in Argentina registered a positive net balance, as well as the categories 3, 6 and 7 in Colombia, 1, 2, 4, 5 and 8 in Mexico. These density classes comprise suburbs of the capital cities, but also small and medium size cities and rural areas in their close proximity.

Chile, however, reports a different pattern where almost no gains or losses were observed during the pandemic in Santiago. However, there was a remarkable negative balance in class 8, while category 9 shows positive values. Patterns in the four countries seem to vary over time according to different levels of restriction, but they also seem to be a bit random in some instances. Generally, positive and negative balances are closer to 0 in late stages of the pandemic. This trend suggests than potential changes on short-distance movements due to COVID-19 could be temporary.

Regarding long-distance movements, those over 100 Km, net balances close to 0 are generally observed in the highest density class during 2020, except in Chile, where we identify a small and temporary net loss which coincides with a small positive balance in density classes 1, 2 and 3. Over the course of the pandemic, net gains in the category 10 increased in the four countries, preliminarily during 2022 where restrictions were completely lifted. This trend mirrors a systematic negative net balances in the category of population density 7 across all the countries, which mainly comprises medium size cities, as well as the class 2 (rural areas) in Chile and Mexico. The increase of net movements in category 10 also coincides with increasing net loss in other classes of population density, such as 4 (small cities) in Argentina, 9 (other large cities rather than Santiago) in Chile, and 3 (small cities) in Colombia.

Collectively, these findings suggest that an urban exodus of long-distance movements did not occur in Latin America. However, large cities seem to have registered lower gains than usual by these type of movements during 2020 and, to a lesser extent in 2021, coinciding when stringency measures were implemented. When restrictions were lifted over 2022, net gains in large cities increased, suggesting that patterns trended to converge to those register before the pandemic.

5.2.1 Comments

> 50km

- Negative net balance in the highest density regions of the metropolitan area in early 2020 for Chile - support of urban exodus but temporarily. The negative net balance in the highest density araes coincides with increases with positive balances in low density areas (class 2 and 3)
- Different patterns in Argentina, Colombia and Mexico - a trend of positive net balances coinciding with negative balances in low density areas (class 2 and 3) - particularly in Colombia and Mexico
- A systematic pattern of negative net balance in medium size cities across all countries (class 7)
- The temporal patterns in the intensity of outflows and inflows are remarkably similar with differences in magnitude.

  < 50km

- Negative net balances in the highest density areas of Argentina, Colombia and Mexico - evidence of a donut effect i.e. negative balance in the core of metropolitan cities
- This pattern coincides with positive balances across different places in the urban hierarchy in these countries.
- Chile reports a different pattern - relatively little change - remarkable is the large negative balance in class 8.

5.3 Movements from and to capital cities

In this section, we explore spatial patterns of outflows under and over 100 Km from the capital cities of Argentina, Chile, Colombia and Mexico during the first wave of COVID-19 in May 2020 and during late stages of the pandemic in March 2022. We identity that both outflows under and over 100 Km away from all cities were much lower in May 2020 than in March 2022, especially from Buenos Aires and Bogota. This finding is consistent to those from Figures 1 and 2 and reinforce that a decline of movements away from large cities occurred in early stages of the pandemic, while levels returned closer to those register before the pandemic after the elimination of stringency measures. However, we find that outflows over 100 Km from capital cities were much more affected by the above-mentioned decline that those under 100km, especially in Argentina Colombia.

We do not observe significant changes in the patterns of internal population movements away from the capital cities between May 2020 and March 2022 in Chile and Mexico. In other works, the distribution of outflows from these cities is mostly the same in both periods. In Argentina and Colombia, however, both movements under and over 100 Km were of shorter distance in May 2020 than in March 2022. Thus, there was a significant decline in the distance that people moved toward the periphery and also to other parts of the country farther away from Buenos Aires and Bogota during early stages of the pandemic.

Our findings suggest that a general drop of movements from large cities occurred in Latin America during the first wave of COVID-19, but the patterns of internal population movements away from these cities were not altered, despite a decline in the distance that people travelled from Buenos Aires and Bogota. Nonetheless, variations seem to have been temporary and did not altered macro-structures of the human mobility in Latin American countries.

6 Discussion

6.1 Summary of key findings

- Decline in mobility intensity after the outbreak of COVID-19
- Support of urban exodus for Chile - but temporary - recovery to pre-pandemic levels
- Donut effect in Argentina, Colombia and Mexico

6.2 Interpretation

Discussion about what we are actually capturing i.e. commuting, shopping trips, etc. vs residential movements / internal migration, and therefore how we interpret the results

6.3 Policy implications

- for housing, transport and planning
- for data

7 Conclusion

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