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Urban mobility patterns and the spatial distribution of infections in Santiago de Chile

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ABSTRACT

The process of a virus spread is inherently spatial. Even though Latin America became the epicenter of the COVID-19 pandemic in May 2020, there is still little evidence of the relationship between urban mobility and virus propagation in the region. This paper combines network analysis of mobility patterns in public transportation with a spatial error correction model for Santiago de Chile. Results indicate that a 10% higher number of daily public transportation trips received by an administrative unit in the city was associated with a 1.3% higher number of confirmed COVID-19 cases per 100,000 inhabitants. Following these findings, we propose an empirical method to identify and classify neighborhoods according to the level and type of risk for COVID-19-like disease propagation, helping policymakers manage mobility during the initial stages of an epidemic outbreak.

1. Introduction

On May 25th, 2020, the World Health Organization (WHO) declared Latin America as the main epicenter of the COVID-19 pandemic after the region’s daily death rate exceeded that of the United States and Europe. Since then, countries in the region have faced various waves of COVID-19 infections. According to the United Nations (2020), the virus in Latin America predominantly affects the most vulnerable populations as the region already has high levels of inequality, informal labor, and fragmented health services. In this context, the region requires attention from the international community. Policymakers must simultaneously support enhanced health care services and design adequate responses to prevent virus propagation during the present and future pandemics. Their designed response must consider sound evidence on COVID-19 contagion patterns and the effectiveness of preventive measures. Vaccination, social distancing, mobility restrictions, wearing a mask, and frequent hand washing, along with effective public oversight that enforces such protocols are among the primary measures implemented to reopen economies while preventing a surge in COVID-19 cases.

Understanding virus propagation poses many challenges to researchers and policymakers. Among them is understanding how the virus spreads across space (Moss et al., 2019). In that regard, available literature looks at mobility patterns when modeling a disease’s propagation (Balcan et al., 2009; Charauudeau et al., 2014; Charu et al., 2017). For example, Stoddard et al. (2013) found that house-to-house human movements underlie the spatial patterns of Dengue virus amplification and spread. In turn, Charauudeau et al. (2014)
provide evidence that commuting volume is positively correlated with the spread of influenza-like illnesses. Moss et al. (2019) showed that larger cities are key propagation nodes of infectious diseases, likely to incubate and expand a virus to national and international levels. In their study, the authors modeled the predictive link between Melbourne’s metropolitan mobility patterns and the level of influenza infections, showing the value of mobility datasets to capture the spatial heterogeneity in transmitting the disease at the urban scale.

Regarding the COVID-19 crisis, studies on China found a positive correlation between confirmed cases at the national level and the total number of passengers traveling outside the Hubei province (Kraemer et al., 2020; Zhao et al., 2020). Zhao et al. (2020) analyzed domestic transportation in China by train, road, and flight, and found a strong association of rail trips with a surge in the number of COVID-19 cases. Zheng et al. (2020) focused on long-haul public transportation specifically, evidencing a positive linkage between trips in all transport modes and the spatial propagation of COVID-19 from Wuhan to 330 cities in China. In the United States, Harris (2020) explored the relationship between subway ridership and virus spatial spread in New York, suggesting that the subway system was a significant disseminator of COVID-19 infection during the initial takeoff of the pandemic. Badr et al. (2020) quantified the relationship between social distancing and virus propagation using mobility patterns between counties in the United States as a proxy for social distancing. Their results show a high correlation between mobility patterns and contagion, suggesting that the benefits from mobility reductions are perceptible between nine days and up to three weeks after implementing mobility restrictions. Applying network science, Chang et al. (2021) simulated the spread of COVID-19 in ten of the largest United States metropolitan areas, finding that a small minority of points in the network would account for a large majority of the infections, and that restricting the maximum capacity at each point of interest would be more effective that uniformly reducing mobility. Carteni et al. (2020) evidenced that mobility habits represented one of the variables that explained the number of COVID-19 cases in Italy, together with the number of tests per day and some environmental variables (i.e., P.M. pollution and temperature). In South Africa, Carlitz and Makhura (2021) used the exogenous variation in province mobility reduction to test the relationship between mobility and virus growth rates, reporting a significant and negative association two weeks after mobility restrictions were implemented.

Despite the spread and impact of COVID-19 in Latin America, there is little research exploring the role that mobility had in virus propagation at the urban level during the early stages of the pandemic. Bennett (2021), who authored one of the few available studies exploring this role, concluded that while quarantine policies implemented in Chile effectively contained virus spread and reduced the number of new COVID-19 cases in high-income municipalities, the effectiveness in low-income municipalities was lower, partially attributed to a lesser level of quarantine compliance measures. This knowledge gap limits policymakers’ ability to design effective plans to contain the spread of future COVID-19-like diseases. Therefore, this paper aims to help close this gap by exploring the relationship between mobility patterns in Santiago, Chile, and the propagation of COVID-19 in the city. Leveraging our results, we propose an empirical method to identify and classify neighborhoods according to their risk of spreading a COVID-19-like disease. This method can guide mobility management during the initial phases of a future pandemic and has the potential to be applied to other cities throughout the world.

The paper is organized as follows: Section II analyzes Santiago’s mobility patterns before and at the beginning of the COVID-19 crisis. Section III presents the methodology to explore the relationship between mobility patterns and the spread of the virus. Section IV presents the results. Section V discusses the findings, and Section VI concludes.

![Job density in Santiago de Chile](Correa, 2020)
2. Background: Mobility patterns in Santiago de Chile

Santiago is the capital city of Chile. The metropolitan area encompasses 52 administrative units and has over eight million inhabitants, equivalent to 41.7% of the country’s population (Ministry of Health, 2020). Each day there are around 18.5 million trips in the city, 4.6 million of which made by public transportation (SECTRÁ, 2014). The main economic, administrative, and academic activities are concentrated in the high-income administrative units of Santiago Centro, Providencia, Las Condes, Vitacura, and Huechuraba (Fig. 1). As a result, these areas attract a high number of trips during morning peak hours and generate a significant volume during evening peak hours. The spatial and time concentration of trips produces enormous stress on the transportation network.

The first confirmed case of COVID-19 in Santiago was announced on March 4th, 2020, in Vitacura. A few days later, more cases were reported in Las Condes, Vitacura, Lo Barnechea, Providencia, Santiago Centro, Independencia, and Ñuñoa, which are administrative units with a high share of total trips in the city (excluding Independencia). Fig. 2 illustrates the date when each administrative unit reached 100 cases per 100,000 inhabitants and shows how rapidly the virus spread towards the other zones of the metropolitan region.

To reduce virus propagation, on March 26th, 2020, the local authorities implemented a quarantine in the administrative units of Lo Barnechea, Vitacura, Las Condes, Providencia, Santiago, Ñuñoa, and Independencia. Consequently, mobility in these areas decreased between 40% and 80%. However, much of Santiago’s population, especially those living in the northern, southern, and central areas, was not affected by the quarantine and continued their daily activities (Fig. 3). Therefore, mobility within the city did not experience a drastic change considering regular mobility patterns, especially compared to other cities that implemented quarantines with a broader geographical coverage. In much of Santiago, public transportation maintained a high level of ridership during the first month of the pandemic.

3. Methodology

To assess whether travel patterns were associated with the spread of the COVID-19 virus in Santiago, we first built the metropolitan...
area’s mobility network. We collected data on mobility patterns from the latest available Origin and Destination Survey (ODS) -year 2012- for 45 administrative units (SECTRA, 2014). Recent studies analyzing transportation in Santiago have used the 2012 ODS, showing that mobility patterns have not significantly varied since 2012 and that the information thereby provided is valid to approximate pre-pandemic mobility trends (Basso et al., 2021; Bennett, 2021; Ministry of Health, 2020).

The dataset includes the 32 administrative units from the province of Santiago, the five administrative units from the province of Talagante, and one administrative unit for each of the provinces of San Bernardo, Calera de Tango, Puente Alto, Pirque, Colina, Lampa, Buin, and Melipilla. The survey contains data on the motive that generated the trip, with working being the essential travel motivator (29.4% of total trips), followed by studying (17.7%), and shopping (16.9%) (Calatayud et al., 2016; SECTRA, 2014). We applied network theory to cast light on the mobility patterns in Santiago metropolitan area and used Gephi to build the mobility network, with nodes being the administrative units of Santiago and connections being the number of trips between a pair of nodes.

Next, we collected data on confirmed COVID-19 cases by April 27th, 2020, for the same 45 administrative units of the metropolitan area (Ministry of Health, 2020). This date was selected considering the moment when the administrative units that concentrate more than 90% of urban population in Santiago exceeded the 100 confirmed cases per 100,000 inhabitants (see Fig. 2), as well as the lagged effect of COVID-19 spatial propagation from when the first mobility restrictions were implemented, which was March 26th, 2020.

Based on this data, we built a model to statistically estimate the association between mobility and the propagation of COVID-19. Mobility increases individuals’ physical proximity, which in the case of airborne diseases raises the probability of getting infected. There are, however, two crucial control variables that correlate with both contagion by proximity and regular mobility patterns, namely:

1. The level of economic activity: Commuting is among the primary motives to travel; in turn, the interaction between individuals increases with business activities. To control for this factor in the model, we used the number of work-related trips received by an administrative unit as a proxy for economic activity. This data was retrieved from the ODS (SECTRA, 2014). In order to test to what extent work-related trips are a good proxy of economic activities, we collected data on the number of landmarks by administrative unit (available in IDE Chile) and estimated the Pearson correlation with work-related trips at the administrative unit level. The correlation is 0.85.

2. Urgent care facilities: The number of these facilities in an administrative unit increases the probability of receiving more infections, but it also strengthens the control measures in the area. Therefore, the association could be in either direction. To control for this, we gathered information on the number of urgent care facilities per administrative unit (Ministry of National
The administrative units with the highest number of healthcare facilities are in the eastern and southern regions of the metropolitan area.

In addition to these controls, we tested the spatial autocorrelation of contagion in the metropolitan area. In the presence of mobility, the contagion rate in a given area tends to be correlated with the contagion levels at its neighboring units. Once we have controlled for spatial autocorrelation, set a proxy for economic activity, and assessed the number of urgent care facilities in an area, we can expect that the predictive link between mobility patterns and the spread of COVID-19, if any, came from higher physical proximity between individuals when they moved across the metropolitan area. Our model specifications are as follows:

\[ C = W^1 C \lambda + X \beta + U_1 \]  
\[ U_1 = W^2 U_2 \rho + V \]

where \( C \) is a \( n \times 1 \) vector that contains the information on COVID-19 confirmed cases per 100,000 inhabitants on April 27th, 2020; \( W^1 \) represents the \( n \times n \) matrix of spatial weights and \( \lambda \) its associated coefficient. \( X \) is an \( n \times k \) matrix with the explanatory variables: total transit ridership (as final trip destination), number of work-related trips, public transportation ridership, private transportation ridership, and the number of urgent care facilities in an administrative unit. Dimensions \( n \) and \( k \) correspond to the number of observations and the number of explanatory variables, respectively. In Equation (2) \( U_2 \) represents the error spatially lagged; \( W^2 \) is a contiguity matrix of dimensions \( n \times n \); and \( V \) is an identically distributed \( n \times 1 \) vector of errors. The model is estimated through maximum likelihood. This method is theoretically more efficient than generalized least squares in two stages when data is normally distributed.

4. Results

Fig. 4 shows Santiago’s public transportation mobility network on a typical day before lockdowns, with each node corresponding to an administrative unit. The node’s size is the sum of the number of trips generated and attracted by the administrative unit, and the width of the link represents the number of trips between the two nodes. According to the optimal cluster identification, the node’s color...
refers to the community it belongs to, based on the degree of connectivity (aka. modularity). Nodes are laid out according to their geographic location in the metropolitan area.

The purple cluster gathers 64.44% of public transportation trips in the metropolitan area. The most central node is Santiago Centro where, together with Las Condes and Providencia, the main economic activities are concentrated. Other relevant nodes in the network are La Florida, Puente Alto, and Maipú, administrative units situated in the periphery of Santiago and that have the highest population rates in the metropolitan area. They are characterized as medium and low-income neighborhoods, where public transportation is often used to commute to offices located in Santiago Centro, Las Condes, and Providencia. The concentration of economic activities in Santiago Centro and its close topological relationship with residential areas such as La Florida, Puente Alto, and Maipú suggests that this administrative unit could play an essential role in spreading an infectious disease to areas of the city. The second cluster of administrative units, in green in Fig. 4, encompasses the northern neighborhoods in the metropolitan area, with mostly low-income families living in the area and accounting for 20% of trips by public transportation. The third cluster, in pink in Fig. 4, corresponds to rural administrative units in the metropolitan area, accounting for 11.11% of the trips. Finally, in brown, a fourth cluster holds 4.45% of public transportation trips for two nodes: Quinta Normal and Cerro Navia.

To further explore mobility patterns by public transportation, Fig. 5 illustrates the network of trips by metro in Santiago. Connections were filtered to include trips with more than 1,200 passengers per day. The size of both links and nodes denotes the same characteristics as in Fig. 4.

The network has five communities. The first holds 44.5% of trips (red) and encompasses metro stations in Line 1, the mainline of the metro network. The link with the highest volume of trips in this cluster is the one connecting the stations of Estación Central and Universidad de Chile, both located in the Santiago Centro administrative unit. Universidad de Chile is also strongly connected to Manquehue, a metro station situated in Las Condes. These three stations attract a large number of work trips from different zones of the city. The second cluster, in green, holds 24.1% of trips and comprises mainly metro stations in Line 5. The most crucial link in this cluster connects Plaza de Maipú and Plaza de Armas stations, the former located in a large western residential area of Santiago and the latter in Santiago Centro. Thus, this link attracts many work-related trips from the western residential area of Maipú and the southern residential area of La Florida. The third cluster, in blue, holds 16.7% of trips and encompasses stations in Line 4. The highest volume of trips in this cluster takes place between Tobalaba station in Providencia administrative unit, a destination for many work trips, and Plaza de Puente Alto, a relevant residential area in southern Santiago. Finally, the fourth cluster, in yellow, holds 14.7% of trips and comprises stations in Line 2, connecting the northern and southern areas with Santiago’s downtown. In the context of an airborne disease outbreak like COVID-19, it is crucial to notice the high connectivity that Tobalaba station has with stations located in different administrative units, such as Santiago Centro, Las Condes, Puente Alto, La Cisterna, and La Florida. Hence, this station could play a key role in the spatial propagation of a virus.

Fig. 6 compares the spatial distribution of trips (6a) and COVID-19 cases in Santiago (6b). On April 27th, 2020, the average number of cases in the metropolitan area per 100,000 inhabitants was 85, with a standard deviation of 42 and a maximum rate of 190, mainly corresponding to the administrative unit of Independencia. The Figure suggests a center-periphery dichotomy where administrative
units in the center are affected the most, and the number of cases decreases when moving towards the periphery of the metropolitan area. The most affected administrative units in the center and eastern areas of Santiago correlate with the mobility patterns described earlier.

Table 1 presents descriptive statistics of the main variables in the study. Table 2 reports the Moran’s I and Geary’s C tests. Statistical evidence of spatial autocorrelation is found at the highest confidence level, suggesting that COVID-19 cases are not randomly distributed across the metropolitan area.

In Fig. 7, we explore in detail the spatial distribution of COVID-19 in Santiago metropolitan area. We illustrate the spatial autocorrelation of COVID-19 cases in the different administrative units. The units in the first and third quadrants report positive spatial autocorrelation. This means that an administrative unit will show a high number of COVID-19 cases if its neighboring administrative units also have a high number of cases. Likewise, if the neighboring units exhibit low contagion, this administrative unit will probably show low contagion as well. In turn, units in the second or fourth quadrant of Fig. 7 report a negative spatial autocorrelation. The names in green indicate that the spatial autocorrelation is significant at a 5% confidence interval. 51% of the administrative units in Santiago reports a significant positive spatial autocorrelation—illustrated by the blue line in Fig. 7. Only Lampa and Colina show a significant negative spatial autocorrelation.

To identify the spatial distribution of the autocorrelation presented in Fig. 7, Fig. 8 presents the administrative units that report a statistically significant spatial correlation according to their type of correlation and their geographical location. Administrative units in yellow have a negative statistically significant spatial autocorrelation, belonging to the second quadrant in Fig. 7. Units in red and blue have a significant and positive spatial autocorrelation, relating to the first and third quadrants in Fig. 7, respectively. Two main geographical clusters are identifiable: in blue are the administrative units that reported relatively low levels of COVID-19, while in red are those with a higher number of cases. The red cluster encompasses metro stations which are critical connectors in the city’s public transportation system. Therefore, they may act as a propagator of COVID-19 to more remote administrative units in the network. The cluster in yellow is a clear example of this scenario: it comprises administrative units with low contagion levels, but these units may be at high risk due to their geographical and topological proximity to the most affected administrative units in the red cluster.

Table 3 summarizes the main results of our models. In the first model, we present the results of a simple linear regression without controls. Then, in the second, third, and fourth models, we control for spatial effects. The estimation by OLS suggests the presence of a relationship between public transportation ridership and the number of COVID-19 cases in an administrative unit. When we control for the number of work-related trips, the number of urgent care facilities, and the spatial autocorrelation, we find that, together with spatial proximity, public transportation ridership associates with the propagation of COVID-19. Model (iii) suggests that a 10% higher number of daily public transportation trips received by administrative unit associates with a 1.3% higher number of confirmed COVID-19 cases per 100,000 inhabitants. In contrast, private transportation does not have a significant relationship with virus propagation. Moreover, a higher presence of urgent care facilities is associated with a decrease in the administrative unit’s contagion rate.

In addition, we explore the possibility of finding size effects of the administrative units by using area, total length of the border, and average length of the border relative to the number of neighbors. In model, (iv) we introduce the logarithm of the length of the border in kilometers—only considering the borders of the metropolitan area of Santiago— as an independent variable. Results show that contagion rates are not altered when considering size effects. Additionally, all coefficients are robust and consistent with what is reported in the model (iii).

Fig. 6. Spatial distribution of trips and COVID-19 cases in Santiago. Sources: ODS (SECTRÁ, 2014) and Ministry of Health (Ministry of Health, 2020).
5. Discussion

Our results show that public transportation was associated with the spatial propagation of COVID-19 in Santiago during the early stages of the pandemic and, as such, would have the potential to spread infectious airborne diseases in the future. Therefore, policymakers should have a deep understanding of how the city’s specific mobility patterns can work as a virus propagation mechanism and implement early risk mitigation measures on buses, metros, and transit stops. Enhancing sanitizing procedures, requiring the

Table 1
Descriptive statistics of the main variables in the study.

| Variable                              | Obs | Mean  | S. D.  | Min  | Max   |
|---------------------------------------|-----|-------|--------|------|-------|
| COVID-19 cases (rate)*                | 45  | 94.61 | 36.23  | 32.97| 189.68|
| Total transportation ridership (thousands) | 45  | 305.64| 302.59 | 31.30| 1566.80|
| Private transportation ridership (thousands) | 45  | 120.38| 125.15 | 7.65 | 591.95|
| Public transportation ridership (thousands) | 45  | 96.58 | 125.62 | 0.62 | 730.54|
| Number of trips for work (thousands)  | 45  | 63.08 | 92.25  | 5.54 | 513.82|
| Urgent care facilities                | 45  | 9.84  | 5.21   | 2    | 24    |

* Note. COVID-19 cases per 100,000 inhabitants by April 27th, 2020.

Table 2
Statistics for spatial autocorrelation.

| Statistic     | Value | Z   | P-value |
|---------------|-------|-----|---------|
| I of Moran    | 0.17  | 8.55| 0.00    |
| C of Geary    | 0.59  | -5.15| 0.00    |

Fig. 7. Moran’s I for spatial contagion at the administrative unit level. Note. Names in green denote a spatial autocorrelation significant at the 5% confidence interval.
mandatory use of masks, setting safe social distancing marks on the ground, and limiting the occupancy per car and bus are some of the actions taken around the world by transit officials to improve passengers’ safety. Related to this, on April 6, 2020, Santiago implemented mandatory mask use on public transportation. Other measures included limiting capacity, increasing ventilation, and strengthening sanitizing procedures at both stations and transit units.

Network theory can be a useful tool for policymakers when evaluating the risk of virus propagation through mobility patterns. Our results for Santiago suggest that the topological proximity of administrative units does not always coincide with geographical proximity. We found that, for example, the centrality of individual nodes, such as the administrative unit of Santiago Centro and the Tobalaba metro station, can play a critical role in spreading the virus towards non-neighboring peripheral areas, which are topologically connected to them given the city’s mobility patterns.

How can we translate these findings into a practical decision tool for policymakers to mitigate the risk of spatial propagation? By using data from the early stages of the COVID-19 pandemic, we develop two indicators to classify administrative units in Santiago and assign a type and level of risk to them:

1. The probability of contagion \( (pc) \) refers to the chance of finding an infected traveler in the administrative unit. It is defined as:
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\[ pc_i = \frac{\text{cases}_i}{\text{originated}_i + \text{received}_i} \]  

(3)

2. Contagion factor \((cf)\) refers to the capacity of an administrative unit to spread the virus throughout the network. It is defined as:

\[ cf_i = \frac{\text{cases}_i}{\text{population}_i \times \text{originated}_i} \]  

(4)

Where the subscript \(i\) refers to the administrative unit, \(\text{originated}\) and \(\text{received}\) refer to the number of trips originated and received by the administrative unit. \(\text{cases}\) are the number of active COVID-19 cases in Santiago on a given day. To illustrate the use of these indicators, we collected data for a day during the first wave of COVID-19 cases in Santiago, specifically May 29th, 2020, but data from any other day could be imputed to the analysis.

Based on these indicators, administrative units in Santiago can be classified into four groups:

- **Group 1**: \((pc_i > \overline{pc}) \& (cf_i > \overline{cf})\), which are the administrative units with the highest risk of virus propagation as they have a high number of COVID-19 cases and play a central role in the mobility network.

- **Group 2**: \((pc_i < \overline{pc}) \& (cf_i > \overline{cf})\), which have a lower number of cases than Group 1, but require close monitoring given the role these administrative units have in the mobility network.

- **Group 3**: \((pc_i > \overline{pc}) \& (cf_i < \overline{cf})\), which have a high number of COVID-19 cases, but do not play a significant role in the mobility network, thus their potential for spatial propagation is low.

- **Group 4**: \((pc_i < \overline{pc}) \& (cf_i < \overline{cf})\), which have a low number of cases and a low capacity to spread the virus spatially, given their peripheral role in the mobility network.

**Fig. 9** maps each administrative unit according to their \(pc\) and \(cf\) levels. The units encompassed by Group 1 are mainly residential areas. Among these areas, Peñalolén, La Granja, Puente Alto, and La Florida should deserve particular attention from policymakers given their high \(cf\). Regarding Group 2, although Santiago Centro, Las Condes, and Providencia had a lower number of cases on May 29th, 2020, they are the center of Santiago’s economic activities, thus they could act as a rapid vector of contagion within the metropolitan area should transmission increase. Finally, Groups 3 and 4 encompassed peripheral areas and presented a limited risk of virus expansion within Santiago.

Policymakers around the world had to face an unprecedented challenge in recent history with the rapid global spread of COVID-19. As the scientific community worked on understanding the characteristics of the virus and develop treatments and vaccines for it, policymakers had to experiment with variety of measures to reduce both propagation rates and the pressure on healthcare systems. In the case of Chile, measures included banning inter-regional mobility, implementing selective lockdowns in administrative units with high contagion rates, issuing a mobility permit, and limiting capacity in public spaces, among others. Moreover, the country started immunizing its population as early as February 3, 2021, achieving an 83.7% immunization rate as of August 20, 2021, one of the
highest around the world. Studies in epidemiology suggest that with increased global connectivity and environmental degradation, pandemics may become more frequent in the next century (Rodó et al., 2021). In this context, governments are already putting in place risk-mitigation plans that encompass i.e., from strengthening early-warning systems to generating prototype vaccines for virus pathogens (Kolata, 2021). Containing spatial propagation through mobility patterns should be among the priority measures to implement at the earliest stages of a pandemic. The tool provided in this paper can help policymakers assess risks and customize interventions to reduce spatial propagation. These findings also encourage further research to discuss health protocols for transportation systems, so they can keep operating without compromising public safety or its critical connector role.

6. Conclusions

This paper provides statistical evidence on the predictive link between mobility patterns and COVID-19 spatial propagation in Santiago de Chile’s metropolitan area. We found that a 10% higher number of public transportation trips received by an administrative unit had an associated growth of 1.3% in the rate of confirmed COVID-19 cases per 100,000 inhabitants. Based on these findings, we suggest a risk-management tool to be implemented at the earliest stages in a pandemic, taking into account two dimensions: (i) the contagion factor and (ii) the probability of contagion of a given spatial unit. The first dimension encompasses units that, because of their network centrality, could propagate the virus faster. The second dimension refers to units with higher level of virus circulation. This rapid classification method can be applied to any metropolitan area. Further work includes expanding the analysis to other cities in Latin America to help fill in the gap on the relationship between mobility patterns and COVID-19 virus spread at the urban level, as a means to identify propagation risks at the transportation network level in the event of future pandemics.

Author contributions

The authors confirm the paper’s contribution: study conception and design: F. Bedoya, A. Calatayud, F. Giraldez, S. Sanchez; data collection. Bedoya, F. Giraldez, S. Sanchez; analysis and interpretation of results: F. Bedoya, A. Calatayud, F. Giraldez, S. Sanchez; draft manuscript preparation: F. Bedoya, A. Calatayud, F. Giraldez. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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