

## Social Mobility Patterns in the World's Populated Cities Through COVID-19

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### Abstract

Objective: identify social mobility patterns in the world's most populated cities from the ravaging pandemic of COVID-19 and the confinement and social distancing measures. Method: ternary diagrams to examine the simultaneous movement to different places (grocery, services, parks, workplaces, residence, and transit). Specifically, we use crosshair ternary plots and a Gaussian Kernel Density Estimator (KDE) for ternary density diagrams. Results: for the most part, the mobility reduction was between 40% and 60% in the selected cities. Nevertheless, there were more significant transit cases, but not workplaces or residences, suggesting that the informal market may absorb part of the labor work. Limitations and implications: the main limitation of this analysis is in scaling the data since the mobility statistics represent negative percentages. Main contribution: the work's principal contribution and originality lie in using ternary diagrams, allowing the identification of social mobility patterns in the largest cities and understanding how displacement of populations has changed since COVID-19.

*JEL Classification: C01, C02, C19, C39, C88.*

*Keywords: COVID-19, mobility, ternary diagrams, populated cities.*

## Patrones de movilidad social en las ciudades más pobladas del mundo durante el COVID-19

### Resumen

El objetivo de la presente investigación es identificar patrones de movilidad social en las ciudades más pobladas a nivel mundial a partir del confinamiento y las medidas de distanciamiento para contrarrestar los efectos del COVID-19. Se utilizan diagramas ternarios para examinar simultáneamente el desplazamiento hacia distintos lugares (bienes, servicios, parques, lugares de trabajo, residencia y tránsito), específicamente, se utilizan diagramas de tipo crosshair y de densidad mediante un Kernel Gaussiano. De manera general, la reducción de movilidad fue entre 40% y 60% en las ciudades seleccionadas, se registran algunos casos con mayor tránsito, pero no hacia los lugares de trabajo o a residencia, por lo que la reincorporación laboral para algunas ciudades se puede estar dando en el mercado informal. La principal limitación se encuentra en el escalamiento de los datos puesto que las cifras de movilidad representan porcentajes negativos. La aportación principal y originalidad del trabajo reside en el uso de los diagramas ternarios, permitiendo identificar patrones de movilidad social en las grandes ciudades y entender la forma en cómo ha cambiado el desplazamiento a partir del COVID-19.

*Clasificación JEL: C01, C02, C19, C39, C88.*

*Palabras clave: COVID-19, movilidad, diagramas ternarios, grandes ciudades.*

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## 1. Introduction

The first registered COVID-19 case was on December 31, 2019, in Wuhan, China. Since then, people's mobility has been reduced due to fear of contagion or mandatory confinement and social distancing measures. At the end of March 2021, around 128 million cases were confirmed worldwide: 44% in America and 33% in Europe, World Health Organization (2021). The pandemic has generated changes in people's mobility, mainly concerning open and closed spaces. The most populated cities have been the most affected ones due to their population's high mobility and the formation of large crowds, contributing to the virus's proliferation.

In that sense, there is a discussion about social distance measures' effectiveness and their consequences on social mobility. After that, the mobility index started to focus on evaluating populations' displacements and their policy implications. According to the World Economic Forum (WEF), there is a positive correlation between income inequality and a country's social mobility, World Economic Forum (2020). Even social media and tech firms such as Twitter, Facebook, and Google started to make their mobility index and movement maps to find mobility patterns and the physical response about distance measures.

Across the massive mobility data generated by institutions, organizations, and firms, this article focuses on two things: 1) social mobility in the world's populated cities as representative metropolises and 2) populations displacements to central areas such as grocery and pharmaceuticals, retail, and recreations, parks, transit, workplaces and residential. This information is generated by the COVID-19 Community Mobility Reports of Google. Mobility reports present daily data of individuals' mobility from 130 countries since February 15, 2020, getting the population's behavior after the countries' restriction measures and their outcomes on the COVID-19 spreading.

We propose an innovative data visualization for Google Mobility Reports through ternary diagrams (also known as simplex or triangle plot). Ternary diagrams represent a three-variable plot that emulates a barycentric coordinate system, meaning that each coordinate is placed at the simplex's vertices. In this case, the vertices triangle plot is represented by population displacements' according to Google's mobility classification. The proportion of each displacement sum to a constant and display a three-variable interaction into a two-dimensional graph. We select the 15 world's populated cities according to the 2020 Annual Demographia World Urban Areas. Nevertheless, Chinese towns had to be omitted since there are no mobility records of this country in Google's reports due to its government's restrictions and policies.

Mixing COVID-19 Community Mobility Reports of Google information on Demographia World Urban Area, this paper aims to identify social mobility patterns in the world's populated cities from the ravaging pandemic COVID-19 and the confinement and social distancing measures. We specifically use crosshair ternary plots and a Gaussian Kernel Density Estimator (KDE). Main findings exhibit principal mobility reduction to open spaces such as retail, parks, and grocery (in a lower proportion). Nevertheless, there are significant differences among countries that drop mobility. Unlike open spaces, results show a more concentrated displacement reduction in transit, residential, and workplaces (40 to 60%) for the most populated cities worldwide.

The analysis is divided as follows: the next section provides a brief but substantial literature review about the relevance of social mobility and its implications since the COVID-19 outbreak. Section 3 refers to the methodological proposal with ternary diagrams to identify social mobility patterns in the world's populated cities; we present crosshair ternary plots and Gaussian Kernel diagrams to analyze patterns in mobility interaction. Discussion, limitations, recommendations, and conclusions are presented in the last section.

The relevance of this study lies in representing originally social mobility during the COVID-19 pandemic using ternary triangles and, secondly, in distinguishing mobility through the outbreak, exhibiting the dramatic reduction of displacement in open and closed areas. Notwithstanding that some cities have mobility patterns, despite health measures, for example, Tokyo and Seoul reduce workplace mobility only by 10% (40 to 60% reduction on average). In contrast, other cities reduced their displacement to workplaces and residences but not in transit (like the cities of India). In this sense, this study offers an innovative way to visualize the interaction between different mobility places and the most populated cities through Google's mobility reports.

## **2. Social mobility and COVID-19**

Social mobility studies have shown the increasing inequality and the governments' opportunity cost for counteracting the pandemic in exchange for sacrificing the economic dynamic and social welfare of their population. However, literature differs on the main factors that prompt the COVID-19 spreading. For example, China's case shows that in large cities, the subway, sewage, and residential garbage are positively correlated with the transmission of the virus and, the urban area and population density are negatively associated with the spread of COVID-19 in the initial stage of the epidemic, Lu (2020). On the other hand, Kraemer et al. (2020) analyze the impact of control measures in China using real-time mobility data from Wuhan, concluding that drastic control measures substantially mitigated the spread of COVID-19.

Other studies supporting that mobility decrease implies decrease spreading of COVID-19 are found in Barbieri et al. (2020); the authors analyze mobility and manners changes due to restrictive measures in ten countries: Australia, Brazil, China, Ghana, India, Iran, Italy, Norway, South Africa, and the United States. An online questionnaire measures the frequency of transport (public and private) and the perceived risks of contracting COVID-19, finding higher negative affections in the people surveyed. For instance, Galeazzi et al. (2020) analyze 13 million Facebook users through geolocated data on how stress affected their mobility patterns in France, Italy, and the United Kingdom. The authors found significant shrink mobility in long trips.

For the United States of America's (U.S.) case, Ruiz-Euler et al. (2020) conclude that mobility undercut occurs at different rates depending on their income level in downtown zones. Those with low incomes show a slower mobility rate for the U.S.'s urban areas than those with higher incomes. Likewise, Engle, Stromme, & Zhou (2020) uses GPS data to determine people's average distance to U.S. counties. Principal findings point out that the counties with a higher population and older adults (+65 years) are more responsive to sanitary measures and social distance methods. Finally, the authors validate virus spreading reduction in counties with Democratic Party preferences.

Furthermore, Chang et al. (2021) introduce a metapopulation model with mobile phone data to simulate the spread of COVID-19 in ten of the U.S.'s largest metropolitan areas. They suggest a few "super-spreading" points for contagion and highlight that disadvantaged groups could not be able to reduce their mobility, being the most exposed in the pandemic. Additionally, Huang et al. (2020) analyze millions of tweets worldwide. They examine for daily and cross-days distance to detect a reduction in human mobility in the U.S.; their results suggest that the mitigation measures' announcements generated mobility changes but in different proportions relying upon the state.

Moreover, Pan et al. (2020) use a set of real-time mobile device location data in the United States (adding Alaska and Hawaii) based on human mobility metrics. The author proposes a Social Distancing Index (SDI) to evaluate the mobility pattern's change regarding COVID-19 spreading at different geographical levels. For Germany, Schlosser et al. (2020) exhibit mobility reduction through mobile phones in travel behavior data. In that sense, restrictive measures led to structural changes in the mobility network. In Tokyo, Yabe et al. (2020) analyze temporary changes in mobility behavior, social contact rates, and positive correlations with COVID-19 transmissibility using mobile phone data and policy restrictions effectiveness.

As stated above, mobile data is critical for social mobility information since it displays people's displacements. For example, Pullano et al. (2020) collect mobile phone data to evaluate the effect of mobility by travel distance, age, and place of residence. Likewise, the authors consider regional data and spatial heterogeneities according to the number of patients who required critical care due to COVID-19. The main findings exhibit the health insufficiencies system and lack of capacity with increasing COVID-19 cases. Further, Aloï et al. (2020) analyze the impact of confinement measures imposed in Santander, Spain, finding that daily mobility is reduced, mainly on trips out of town.

Regarding travel behavior, Borkowski et al. (2021) analyze the impact of COVID-19 on daily mobility data in Poland through surveys. The authors found that the greater the fear of contagion, the shorter time-traveling is. Other results suggest that the closure of borders worldwide led to Serbia's massive return since the emergency declaration in March 2020. The analysis highlights how Serbs who worked outside the country lost their income and students studying abroad Pešić (2020). The literature exposed shows some of the data information collected to analyze social mobility; in that sense, we introduce some available open sources and their differences to highlight Google Social Mobility Reports effectiveness in our methodology.

The literature shows different case studies for countries, cities, and regions. However, we consider that under analyzing the world's populated cities, a visualization of mobility patterns can be represented, showing both the coincidences and the regions' heterogeneities. In this sense, the following section shows the methodological structure of our analysis.

### **3. Methodology**

Ternary diagrams have been used primarily in engineering, physics, medicine, biology, to name a few but not directly to social science. For example, Nesbitt et al. (2017) analyze the relationship between dinosaurs and reptiles) while Chu, Ma, Prince, & al. (2017) use ternary diagrams to study human

microbial communities. Likewise, Kalenitchenko et al. (2016) para use ternary plots to analyze microbial bacteria in wood, and Wenger, Buzgariu, & Galliot (2016) explore the regulation of neurogenic genes in animals. Meanwhile, Briffaa et al. (2020) apply ternary plots to determine the fighting capacity in animals. Triangle plots are also well known in air pollution studies Zahari et al. (2016), migratory flows between countries of the European Union Nowak (2020), or even to understand the origins of the three-dimensionality of drugs Meyers et al. (2016) or the rupture of a nucleus into fragments of unequal masses Smit et al. (2017) among others.

Nevertheless, there are no mobility studies developed with this tool; in that sense, our research is relevant and pioneering in using this technique.

### 3.1 Data classification

The social mobility data of people that live in large cities implemented for this inquiry was collected from Google's COVID-19 Community Mobility Reports<sup>3</sup>. Using their mobility classification, we split it into two groups, open and closed spaces, as shown in Table 1:

**Table 1.** Social Mobility classification according to open and closed spaces

Open spaces	Closed spaces
<b>1. Grocery &amp; Pharmacy</b>	<b>1. Transit stations</b>
Grocery & pharmacy: Mobility trends for grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.	Transit stations: Mobility trends for places like public transport hubs such as subway, bus, and train stations.
<b>2. Parks</b>	<b>2. Residential</b>
Parks: Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.	Mobility trends for places of residence.
<b>3. Retail &amp; recreation</b>	<b>3. Workplaces</b>
Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.	Mobility trends for places of work.

Source: author's elaboration. Mobility definitions are expressed the same as Google's COVID-19 Community Mobility Reports.

According to data from the first semester of 2020, Demographia World (2020), the cities used for the study were the most populated globally, measured by their estimated population and population density per kilometer, as shown in Table 2.

<sup>3</sup> Available at <https://www.google.com/covid19/mobility/?hl=es>

**Table 2.** World's populated cities

	Country	Urban Agglomeration	Population Estimate (thousands)	Urban Population Density per Square Kilometer
1	Japan	Tokyo	37,997	4,614
2	Indonesia	Jakarta	34,540	9,756
3	India	Delhi	29,617	13,266
4	India	Mumbai	23,355	24,773
5	Philippines	Manila	23,088	12,330
6	China	Shanghai	22,120	5,436
7	Brazil	São Paulo	22,046	7,076
8	South Korea	Seoul	21,794	7,871
9	Mexico	Mexico City	20,996	8,802
10	China	Guangzhou	20,902	4,815
11	United States of America	New York	20,870	1,700
12	China	Beijing	19,433	4,658
13	Egypt	Cairo	19,372	9,639
14	India	Kolkata	17,560	12,988
15	Russia	Moscow	17,125	2,908

Source: author's elaboration with 16th Annual Demographia World Urban Areas.

It must have emphasized that Chinese cities are omitted from the study since there are no records in Google's COVID-19 Community Mobility Reports. In that sense, we only use 12 of the 15 most populated cities. Google's Mobility Reports compute daily data from the median value of length and visit frequency to trendy places compared to January 3, 2020, to February 6, 2020, as a benchmark. Table 3 displays the mean values of social mobility from January 15 to December 31, 2020, and January 1, 2021, to March 11, 2021 (the last data of this study).

**Table 3.** Mean values of social mobility (Google's baseline)

Year	City	Retail	Grocery	Parks	Transit	Workplaces	Residential
2020	Tokyo	-27%	-3%	-14%	-34%	-24%	-12%
2021	Tokyo	-19%	-5%	-20%	-33%	-17%	-8%
2020	Jakarta	-34%	-12%	-57%	-43%	-30%	-14%
2021	Jakarta	-33%	-13%	-52%	-42%	-33%	-11%
2020	Delhi	-50%	-25%	-65%	-46%	-41%	-16%
2021	Delhi	-33%	-7%	-34%	-21%	-25%	-7%
2020	Mumbai	-63%	-30%	-69%	-65%	-51%	-20%
2021	Mumbai	-43%	0%	-41%	-35%	-28%	-9%
2020	Manila	-53%	-23%	-48%	-64%	-46%	-24%
2021	Manila	-40%	-6%	-31%	-57%	-34%	-19%
2020	Sao Paulo	-40%	-3%	-30%	-33%	-24%	-14%
2021	Sao Paulo	-37%	-5%	-25%	-28%	-18%	-10%
2020	Seoul	-16%	-6%	-34%	-11%	-9%	-5%

2021	Seoul	-14%	-11%	-5%	-16%	-14%	-8%
2020	Mexico City	-44%	-15%	-43%	-42%	-34%	-16%
2021	Mexico City	-33%	-6%	-42%	-38%	-24%	-11%
2020	New York	-62%	-29%	-34%	-57%	-50%	-17%
2021	New York	-66%	-33%	-55%	-60%	-52%	-18%
2020	Cairo	-31%	-5%	-28%	-22%	-19%	-8%
2021	Cairo	-19%	-25%	-23%	-6%	-12%	-4%
2020	Kolkata	-56%	-31%	-70%	-52%	-41%	-17%
2021	Kolkata	-33%	-12%	-41%	-15%	-22%	-8%
2020	Moscow	-13%	0%	-20%	-12%	-20%	-3%
2021	Moscow	-30%	-18%	-36%	-23%	-29%	-7%

Source: author's elaboration.

Table 3 shows the mobility shrinkage for the most populated cities. Cities like Mumbai, Kolkata, Manila, New York, and Mexico City observed a notable mobility reduction to retail and recreation activities in 2020 (-40% to -50%). The less mobility reduction was to grocery and pharmaceutical stores overall (-5% to -25%). Park's mobility contraction is notable in Jakarta, Mumbai, Delhi, Kolkata, and Mexico City in 2020 (-50% to -70%). New York observes the most significant mobility transit reduction in 2020 (-57%) compared to Seoul (-11%). Mobility to workplaces and residential areas is quite different; for example, Asian cities (excluding Seoul and Tokyo) registered the highest workplace mobility reduction than Latin American and African cities. Finally, residential displacements have a minor decrease due to confinement measures.

Contractions in mobility continue in 2021 but less than 2020 since the implementation of vaccination campaigns and the relaxation of sanitary measures. To present mobility's changes in 2020 and 2021, the following section presents ternary diagrams.

### 3.2 Ternary diagram

Ternary diagrams, also known as ternary plot, simplex plot, Finetti diagram, triangle plot, or Gibbs composition triangle, represent three-variable onto a 2D field. Specifically, ternary diagrams emulate a barycentric coordinate system, meaning that each coordinate is placed at the simplex's vertices and the ternary plot is a particular case (Kawabata & Shimura, 2019). For this analysis, each point within the ternary diagram indicates mobility to the open and closed places classification (table 2). Since we can only use three variables, triangle plots will be classified from open and closed displacements and ordered by cities population split by two groups: from Tokyo to Sao Paulo and Mexico City to Moscow<sup>4</sup>.

$$1^{\text{st}} \text{ Triangle: } aG + bR + cP = 100\%$$

$$2^{\text{nd}} \text{ Triangle: } dW + fT + gRes = 100\%$$

Where:

$G$  = Grocery and pharmaceutical mobility

$R$  = Retail and recreation mobility

<sup>4</sup> The reason for ordering the cities into two groups is to provide further clarity to the ternary performance.

$P$  = Parks mobility  
 $W$  = Workplace mobility  
 $T$  = Transit mobility  
 $Res$  = Workplace mobility

Such that the three apexes represent 100% $G$ , 100% $R$ , and 100% $P$  of the 1<sup>st</sup> triangle and 100% $W$ , 100% $T$ , and 100% $Res$  for the second triangle. Both triangles are equilaterals, and each coordinate axes are scaled:

$$0 \leq G, R, P \leq 1$$

$$0 \leq W, T, Res \leq 1$$

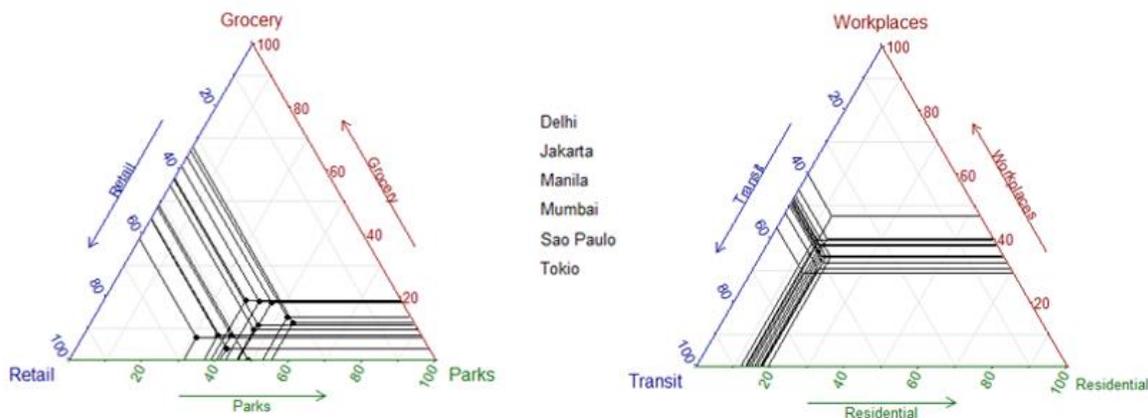
Likewise, variables are scaled with a normalization process:

$$S = \frac{x_i - \mu}{\sigma} \tag{1}$$

Where  $S$  refers to the scaled data,  $\mu$  is the mean of each observation, and  $\sigma$  is the standard deviation. This process allows mobility displacements' variables to be scaled and centered with  $\mu = 0$  and  $\sigma = 1$ . Since negative values are not allowed, and Google's Mobility Reports show non-positive percentages, we use the absolute yearly mean values of social mobility to understand that plotted values refer to mobility contraction.

## 4. Results

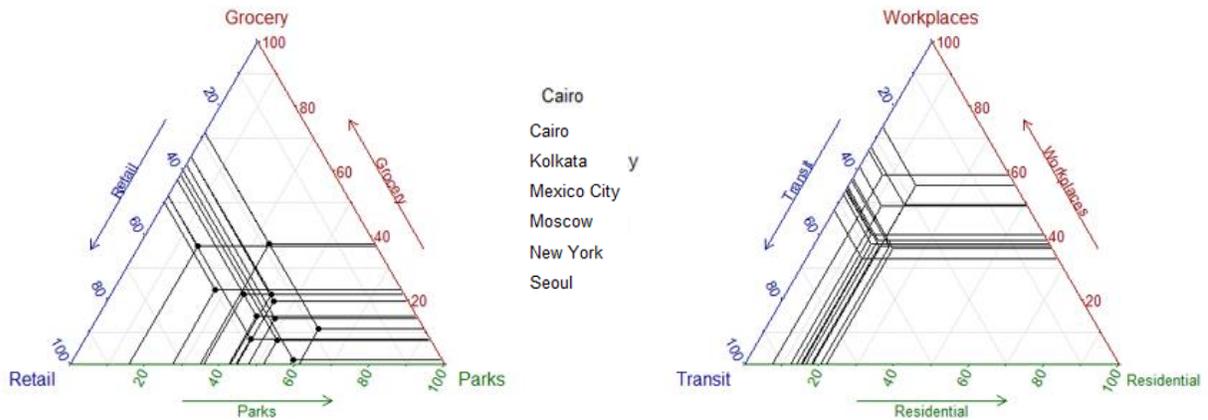
Figure 1 displays crosshair ternary plots for open places where each point represents the mean absolute value from January 15 to December 31, 2020, and January 1, 2021, to March 11, 2021 of cities group 1 and 2. Gridlines for coordinate axes of both triangles are  $\frac{1}{5}$ .



**Figure 1.** Crosshair ternary plot for group 1

Source: author's elaboration based on (Hamilton, 2020) in R programming language.

Figure 1 represents each data point (mean absolute value) of social mobility to the marks ( $G, R, P, W, T, Res$ ) on the respective axes. Since data is scaled, we can match and have a new visualization of mobility interaction. The first group of cities integrated by Delhi, Jakarta, Manila, Mumbai, Sao Paulo, and Tokyo, observed a retail mobility reduction from 40% to 60%, while park displacements shrank between 35% and 65%. Grocery and pharmaceuticals reflect less mobility reduction (5 to 20%), making sense; people have to buy goods and supplies for their homes and buy medicines despite the confinement. Likewise, it is observed a transit reduction for the first group from 40% to 60% connected to workplaces shrink mobility of 30% to 50%. Residential mobility reflects only a 20% reduction given the policies of social distancing and the displacement of work in residential areas. Figure 2 shows the crosshair plot for group 2.



**Figure 2. Crosshair ternary plot for group 2**

Source: author's elaboration based on (Hamilton, 2020) in R programming language.

Even both groups represent the most populated cities, the second sample integrated by the Cairo, Kolkata, Mexico City, Moscow, New York, and Seoul shows disparities in mobility concentrations. For instance, retail mobility decreased from 30% to 50%, but parks' mobility display mobility reductions from 20% to 40%, parallel to a 40% drop in grocery places. The more significant the decrease in parks' mobility, the lower the grocery mobility is. Alake the first group, mobility to workplaces, transit, and residential are similar; however, transit movement decrease has a more comprehensive threshold from 25% to 55%, and residential mobility is less than 20% in most cases. It is worth highlighting that significant workplace mobility drop is linked to low transit reduction, suggesting that the informal market may absorb part of the labor work, especially for the cities that fall within emerging countries.

We use a ternary density plot based on a Kernel Density Estimator (KDE) to show the mobility relationship among cities. Following Chen, Huang, & Zhang (2020) notation, the KDE for each mobility classification is defined as:

$$\begin{aligned} \widehat{f}_K(G, R, P) &= \frac{1}{nh_{n1}nh_{n2}nh_{n3}} \sum_{i=1}^n K\left(\frac{X_{i1-G}}{h_{n1}}, \frac{X_{i2-R}}{h_{n2}}, \frac{X_{i3-P}}{h_{n3}}\right) \\ \widehat{f}_K(W, T, Res) &= \frac{1}{nh_{n1}nh_{n2}nh_{n3}} \sum_{i=1}^n K\left(\frac{X_{i1-W}}{h_{n1}}, \frac{X_{i2-T}}{h_{n2}}, \frac{X_{i3-Res}}{h_{n3}}\right) \end{aligned} \quad (2)$$

Where  $f_K$  refers to the ternary KDE of  $(G, R, P)$  and  $(W, T, Res)$ ;  $(X_{11}, X_{12}, X_{13}), (X_{21}, X_{22}, X_{23}), \dots, (X_{n1}, X_{n2}, X_{n3})$  are the social mobility samples of the three-dimensional plot and  $h_{n1} > 0, h_{n2} >, h_{n3} > 0$  are constants bandwidths related to  $n$  cities samples and  $(G, R, P)$  and  $(W, T, Res)$  are valued by splitting the cube space with the maximum and minimum values of  $(G, R, P)$  and  $(W, T, Res)$ . Kernel function is denoted as:

$$K(\cdot) = \sum_{d=1}^3 K_d(\cdot) \tag{3}$$

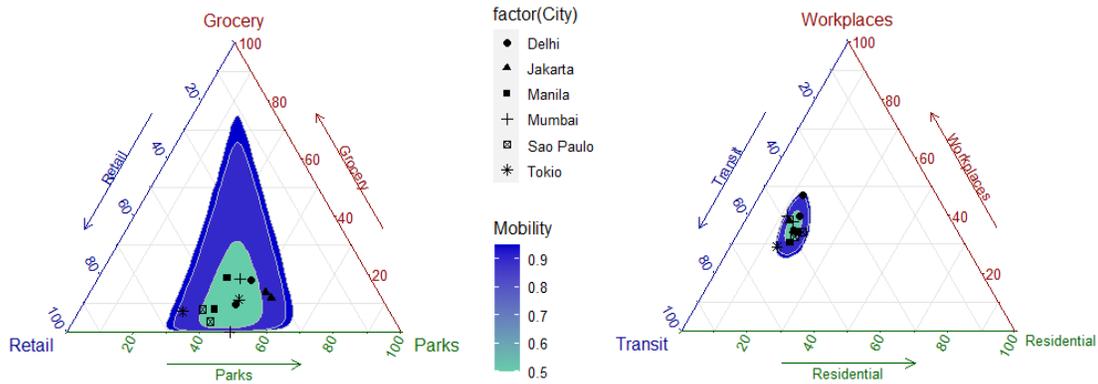
Where the Kernel function is represented by  $K(\cdot)$  and  $(d = 1,2,3)$  relates to samples' number. Since mobility displacements' variables are scaled and centered with  $\mu = 0$  and  $\sigma = 1$ , we use a Gaussian Kernel for the symmetric ternary KDE:

$$Kd(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right), \quad d = 1,2,3. \tag{4}$$

Finally, the ternary KDE density plot for social mobility is expressed as follows:

$$\begin{aligned} \widehat{f}_K(G, R, P) &= \frac{1}{n(\sqrt{2\pi})^3 \prod_{d=1}^3 h_{dn}} \sum_{i=1}^n \exp\left\{-\left(\frac{X_{i1} - G}{\sqrt{2h_{n1}}}\right)^2 - \left(\frac{X_{i2} - R}{\sqrt{2h_{n2}}}\right)^2 - \left(\frac{X_{i3} - P}{\sqrt{2h_{n3}}}\right)^2\right\} \\ \widehat{f}_K(W, T, Res) &= \frac{1}{n(\sqrt{2\pi})^3 \prod_{d=1}^3 h_{dn}} \sum_{i=1}^n \exp\left\{-\left(\frac{X_{i1} - W}{\sqrt{2h_{n1}}}\right)^2 - \left(\frac{X_{i2} - T}{\sqrt{2h_{n2}}}\right)^2 - \left(\frac{X_{i3} - Res}{\sqrt{2h_{n3}}}\right)^2\right\} \end{aligned} \tag{5}$$

Figure 3 display the ternary density plot for the first sample of cities. Density inside the triangle exhibits mobility displacements and interaction among towns in 2020 and the first quarter of 2021. Delhi reveals a 60 to 80% reduction in retail mobility, 50 to 60% in parks, and 10 to 20% in grocery and pharmaceuticals. Jakarta, for instance, did not present significant changes between 2021 and 2021Q1 in retail (around 80%), parks (60%), and grocery mobility (approximately 20%); Manila shows a slight change in retail (90% to 80%), parks (50 to 40%) and a more substantial change in grocery mobility (10 to 30%). Likewise, Mumbai exhibits the most significant mobility contraction (more than 90% to 80% in 2021Q1), parks are similar (50%), and grocery from 20 to 5%). Sao Paulo shows retail displacement reductions around 90%, 40% in parks, and 10% mobility decrease in grocery stores. Finally, Tokyo shows a reduction from 80 to 90% on retail, a more significant mobility reduction in parks (50% in 2020 and 35% in 2021Q1), and a 15 to 10% reduction in grocery.



**Figure 3.** Ternary density plot for group 1

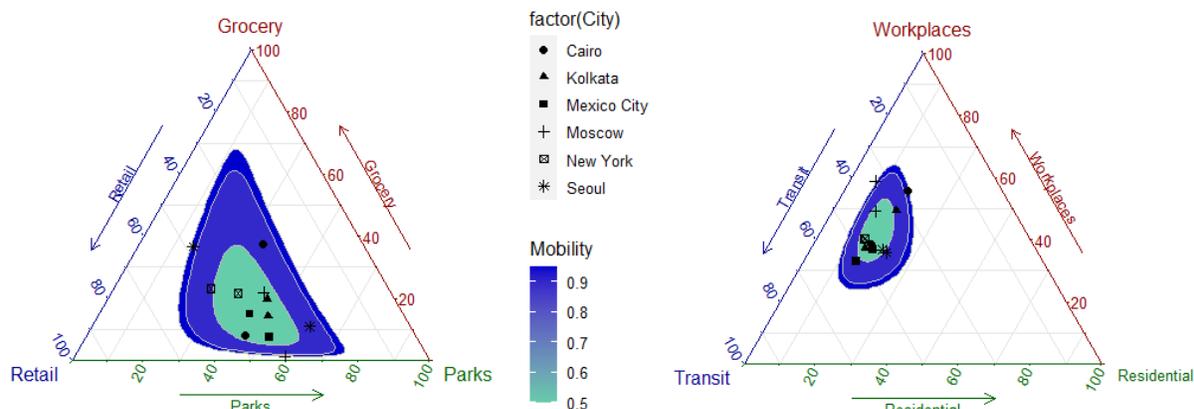
Source: author's elaboration based on (Hamilton, 2020) in R programming language.

Likewise, figure 3 represents the density diagrams for workplaces, transit, and residential spots. For these places, mobility reduction is concentrated in similar thresholds for most of the cities. Transit reductions are between 45 to 70%, where Delhi presents the less mobility contraction (45%) and Tokyo the most remarkable reduction (70%). Residential displacements are between 25 and 40% for the first sample of populated cities, while workplace mobility reveals a decrease between 30 and 50%; it is noteworthy that Tokyo displays less reduction (around 30%) in workplace displacements.

Moreover, figure 4 displays the ternary density plot for the second group of most populated cities. Unlike the first group, Cairo, Kolkata, Mexico City, New York, and Seoul shows a broader displacement density: Seoul presents the most significant mobility change in retail (85% in 2020 to 60% in 2021Q1), 65% to 35% reduction in parks and 40% to 60% grocery mobility in the first quarter of 2021. Like Seoul, Cairo city exhibit a decrease of 85 to 60% in displacement in retail and recreation, no significant changes in parks (around 50%), and a 40 to 10% reduction in grocery translations. Kolkata shows minor changes in mobility: 80% for retail, 60% in parks, and 20% for grocery stores. Mexico City exhibits a retail mobility reduction of around 90% in 2020 to 80% in 2021Q1. Likewise, there is a 60 to 50% drop in parks and a 20 to 10% decrease in grocery mobility. New York has similar displacement reductions for retail in 2020 and 2021Q1 (80%), 50 to 40% mobility reduction to parks, and 30% average reduction to grocery places.

For the second-density plot in figure 4, mobility to transit, workplaces, and residential is also concentrated like the first group; nevertheless, there is a greater distance. For instance, Cairo shows a mobility reduction in transit of 60% in 2020 and 40% in 2021Q1, residential drop 45% to 30%, and workplaces displacement from 60% to 40%, respectively. Kolkata exhibits a reduction of 60% to 40% in transit, 40 to 60% in residential, and 40% to 60% in workplaces mobility. Mexico City shows a displacement shrink of around 60% in 2020 and 2021Q1, while residential exhibits a reduction between 30 and 40%. Finally, workplaces mobility in Mexico City was approximately 40%. For Moscow, transit reduction is between 40 to 60%, for residential stays is 40%, and workplaces mobility decrease by 60 to 40%. New York exhibits a similar mobility decrease in both periods for transit (60% on average) and 40% in residential and workplaces. Comparable to New York, Seoul

shows a similar displacement shrink: 60% in transit and 40% reduction in residential and workplaces.



**Figure 4.** Ternary density plot for group 2

Source: author's elaboration based on (Hamilton, 2020) in R programming language.

## 4.1 Discussion Remarks

To the best of our knowledge, this is the first study of this kind categorizing social mobility with ternary diagrams. The studies examined in the literature review are looking for novel proposals about mobility's measurement and the implications for individuals throughout and after COVID-19. Nevertheless, most of the literature referred to in this document are aimed at detecting mobility patterns from the mobile phone data and the surveys conducted in the different countries to:

1. Correlation between COVID-19 transmission and mobility measured through mobile app and social media (Lu, 2020), (Kraemer et al. 2020), (Barbieri et al. 2020), (Chang, et al. 2021), (Huang et al. 2020) and (Pullano et al. 2020).
2. Stress level through confinement (Galeazzi et al. 2020).
3. Verify the effectiveness of health measures through confinement (Pan et al. 2020), (Schlosser et al. 2020), (Yabe et al. 2020) and (Aloi et al. 2020).
4. To confirm which are the most vulnerable sectors and the most affected places by the mobility reduction (Ruiz-Euler et al. 2020) and (Borkowski et al. 2021).

Unlike these studies, the implementation of ternary graphs with the information generated by Google Reports, both in its crosshair form and with the KDE, allowed us to obtain an innovative visualization of the dynamics and interaction in the social mobility of the most populated cities. There were confirmed common patterns in displacement reduction for specific places. Furthermore, we also understand their heterogeneity, where they move the more, and how cities interact. In that sense, we offer an original result in its visualization and robustness of the implemented diagrams.

## 5. Conclusion

This study aims to identify social mobility patterns in the world's most populated cities through COVID-19, along with the confinement and social distancing measures. The way people live, work and interact changed dramatically since the confinement and social distancing measures due to the pandemic of COVID-19. One of the significant consequences can be seen in the social mobility for all nations. In that sense, different approaches try to find mobility patterns to analyze physical reactions to COVID-19 policies and to understand displacement relationships to evaluate the implications in the economy. Nevertheless, most of the analyses using mobility data are focused on behavioral effects (which is not bad at all) but no to analyze mobility contraction in the most populated cities as a representation of mobility shrinkage and its gradual recuperation in 2021.

We use COVID-19 Community Mobility Reports of Google to show mobility patterns in an innovative visualization for the world's populated cities (a sample of 12) divided into two mobility groups: 1) retail and recreation, parks and grocery (open spaces), and 2) transit, workplaces and residential (closed spaces). We use ternary diagrams to reach our goal through crosshair and Kernel Density Plots (KDE). Ternary diagrams represent three-variable onto a 2D field and emulate a barycentric coordinate system. In this analysis, each point within the ternary diagram indicates mobility to the open and closed spots classification.

Our main findings reveal significant differences among countries in mobility reduction. Cities like Mumbai, Kolkata, Manila, New York, and Mexico City observed a notable displacement drop to retail and recreation activities in 2020 (-40% to -50%). The less mobility reduction was to grocery and pharmaceutical stores overall (-5% to -25%) while Park's mobility contraction is notable in Jakarta, Mumbai, Delhi, Kolkata, and Mexico City in 2020 (-50% to -70%). New York observes the most significant mobility transit reduction in 2020 (-60% on average) compared to Seoul (-10%). Mobility to workplaces and residential areas is quite different; for instance, Asian cities (excluding Seoul and Tokyo) registered the highest workplace mobility reduction compared to Latin American and African cities. Finally, residential displacements are concentrated around 40% reduction for all cities.

One limitation of our work is in data transformation and scale since ternary diagrams do not allow negative numbers (mobility reduction are represented by negative percentages). We solved this problem using the absolute yearly mean values of social mobility to understand that plotted values refer to mobility contraction. Likewise, it is worth comparing different measure distances like the Mahalanobis distance for further ternary plots implementation. Despite these considerations, results are consistent with the method performed. For now, we believe that this is one of the many ways that ternary plots can be implemented in social sciences analysis. For further works, we will extend ternary diagrams assessment to find patterns in financial data.

The detection of mobility patterns presented in this document allows us to explain how and where people are moving. Firms like Google take this information to generate consumption and advertising profiles based on their mobility. On the government side, this can be a channel to strengthen the regulations about home-office. It permits identifying which places may represent a greater risk in terms of contagions regarding open spaces for families and individuals. In that sense, the work's principal contribution and originality lie in using ternary diagrams, permitting the

identification of social mobility patterns in the largest cities, and understanding how displacement of populations has changed since COVID-19.

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