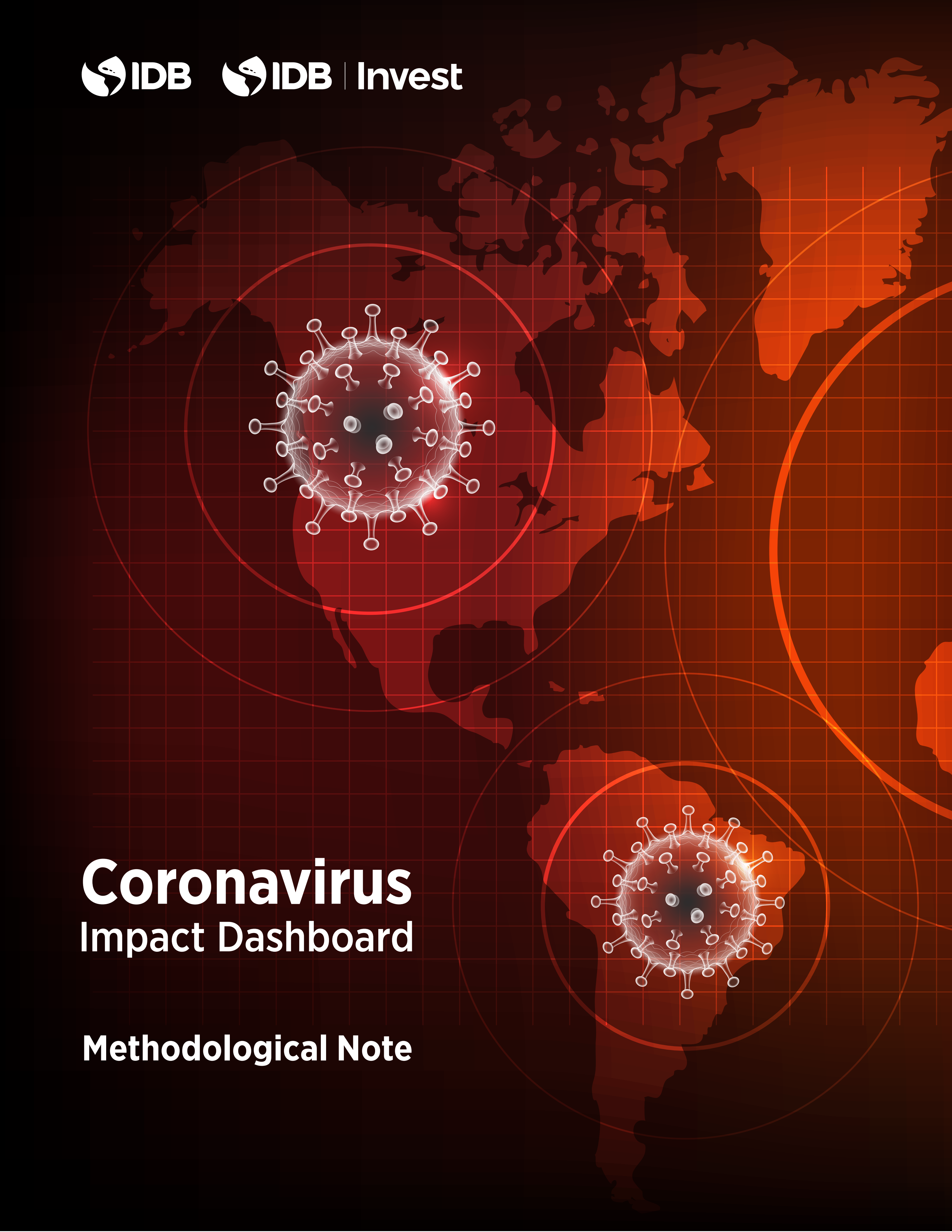

IDB IDB | Invest

Coronavirus
Impact Dashboard

Methodological Note

The IDB and IDB Invest Coronavirus Impact Dashboard
Methodological Note

Initial creation: 3/21/2020
This version: 4/27/2020
Version: 2.0

I. The Coronavirus Impact Dashboard

The Coronavirus Impact Dashboard has been created by the IDB and IDB Invest to track in real time the impact of the coronavirus disease 2019 (also known as COVID-19) on the countries of Latin America and the Caribbean. The dashboard aims to track a range of variables of interest in order to provide policymakers, epidemiologists, and the general public in the region with measures of the impact that "social distancing" restrictions and recommendations due to the coronavirus outbreak are having on the population and on economic activity.[1]

Currently the dashboard provides measures of the impact on traffic congestion, public transport use, human mobility, air quality and daily statistics on COVID-19 cases at the country level or disaggregated levels when available Depending on the data source, data provided in the dashboard will be continuously updated (daily or weekly) in order to track real-time impact.

This Methodological Note will also continuously track and update methodological changes (when necessary) and changes/additions to data sources.[2] The version of the Methodological Note and its date of creation are shown at the top of the document.[3]

[1] To cite the IDB and IDB Invest Coronavirus Impact Dashboard, please use the following reference: Inter-American Development Bank and IDB Invest. "IDB and IDB Invest Coronavirus Impact Dashboard". 2020. *Inter-American Development Bank.*www.iadb.org/coronavirus-impact-dashboard

[2] To cite this Methodological Note, please use the following reference: Inter-American Development Bank and IDB Invest. *IDB And IDB Invest Coronavirus Impact Dashboard Methodological Note*. Washington, DC: Inter-American Development Bank, 2020. https://iadb-comms.org/IDB-IDBInvest-coronavirus-impact-dashboard-methodological-note.

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II. Changelog

- **Version 2.0 Changes**

1. Methodological changes in Traffic Congestion Intensity (TCI) calculation (see Section IV):
    a. Changed baseline dates from March 1-7, 2020 to March 2-8, 2020.
    b. Changed data in TCI calculation from using jams that appeared only once if there was no change in delay/length, to all jams being counted once in each 5-minute period.
    c. Dropped from TCI calculation jams associated to closed streets.
    d. Changed rules for reporting a particular region in the Dashboard, from being based on the relationship between TCI and population, to a rule based on i) historical variability; ii) historical TCI relationship with Open Street Map road network length.
    e. Added reporting of weekly TCI measure to the Dashboard.
2. Added tabs in Dashboard for Human Mobility and Air Quality.
3. Expanded and modified reporting of public transport data: i) report more detailed Moovit data; ii) changed public transport baseline week to be March 2-8, 2020, iii) added public transport data for Bogotá and São Paulo.

III. Data sources

- **COVID-19 cases and deaths**

The data on COVID-19 cases and deaths is compiled by the Center for Systems and Science Engineering (CSSE) at John Hopkins University. Their information comes from several different sources, which might differ in terms of reliability. We take this data on an "as-is" basis, as provided by the CSSE. The original data can be found here.

- **Traffic congestion data**

The IDB Group has an agreement with Waze through the Waze for Cities Program. The agreement provides us with access to aggregate-level information originating from a continuous feed every two minutes from the Waze community-driven navigation app. This feed provides information on traffic jams and user alerts. (See below for details on the traffic measures created from these data.)

- **Public transport data**

We rely on different data sources to measure public transport use:

1. Bogotá BRT and bus system: We use data on validations (i.e., ticked card swipes at BRT stations) for Transmilenio and the SITP-Buses (i.e., ticket card swipes when boarding the Bus). We obtain the data from Transmilenio's open data website. We report the percentage change in validations, compared to the validations in the week of March 2-8, 2020.
2. Lima BRT: We use data on daily validations (i.e., ticket card swipes at stations) for the *Metropolitano*, a bus line in Lima, Peru. We obtain the data from the Instituto Metropolitano PROTRANSPORTE de Lima of the Municipality of Lima. We report the percentage change in validations, compared to the validations in the week of March 2-8, 2020.
3. São Paulo Bus System: We use data on daily validations (i.e., ticket card swipes and single cash paid tickets in the buses) for the São Paulo Bus System. We obtain the data from the Secretaria Municipal de Mobilidade e Transportes of the Municipality of São Paulo. We report

the percentage change in validations compared to the validations in the week of January 15, 2020. We present the results for both total validations and validations classified by the city as free rides (it includes, among others, validations of people over 60 years old and people with disabilities; it does not include students).

4. Moovit: The public transport app Moovit generates the Moovit Public Transit Index for almost 100 cities across the world. We report the overall percentage change in public transport use as a result of the coronavirus crisis for the cities in Latin America and the Caribbean for which Moovit reports the index. We re-calculate Moovit's index so that the percentage changes reported are compared to the week of March 2-8, 2020.

- **Human mobility data**

In the Dashboard we present summary measures from the Human Mobility Map which is based on data from Veraset. The Human Mobility Map is generated by the IDB in an effort coordinated by the Research Department. For methodological details see here. And for more information about this initiative see this blog.

- **Air quality data**

The air quality measures are based on modified Copernicus Sentinel data. Launched in 2017 by the European Space Agency (ESA), Copernicus Sentinel 5P monitors the density of several atmospheric gases, aerosols, and cloud distributions affecting air quality and climate. The measurements are made by an instrument called TROPOspheric Monitoring Instrument (TROPOMI). TROPOMI measures a wide range of atmospheric trace gases such as nitrogen dioxide (NO_2), ozone (O_3), sulphur dioxide (SO_2), methane (CH_4), and carbon monoxide (CO). The data can be found on the Copernicus open access hub.

IV. Methodology

- **Traffic congestion**

1. Interpreting Waze data

a. Waze data on traffic jams are passively generated while the Waze app is running on a user's device (i.e., even if the user is not actively using it).

b. Combining that information for all Waze users ("Wazers") in the area, Waze identifies whether at any given geographic point traffic is slowing down (with respect to the expected speed under no-jam conditions, or "free-flow").

c. It must be noted that a "no congestion scenario" does not necessarily imply that there is no traffic on a specific road. This is because while congestion is obviously correlated with the volume of vehicles, the relationship between speed and volume is not linear (see Highway Capacity Manual, Level of Service). Even when congestion is reduced to zero there may still be vehicles driving on the road. The Waze data do not allow saying anything about the volume of vehicles on the road under a no-congestion scenario. An extreme example can illustrate this point: if there were only autonomous and connected vehicles on a given road, at a volume consistent with the road specifications, traffic congestion would be zero, but the number of vehicles could still be significant. In a more realistic scenario (we do not have many autonomous vehicles roaming the streets yet), one would expect traffic congestion to be highly correlated with vehicle volume (traffic) at high volume levels, but once traffic is "free-flowing", Waze data (and the traffic congestion measure presented below) would not be able to capture it.

d. From the information generated by the app's use Waze creates "jam lines" that indicate continuous portions of streets where speed has slowed. Waze data provides the exact geographic location, length, speed, and time delay for these jam lines compared to the time it would normally take to transverse the jam line by car. A categorization for the severity of the jam is also provided.
e. Thus, the jam data is composed of jam lines (which can change over time) measured at different time intervals. Given the crowd-sourced nature of the data, it cannot be determined if fluctuations in jam line activity are due to actual changes in traffic conditions or due to fluctuations in the number of active Wazers. Evidence from on-the-ground measures supports the notion that changes in jam activity are generally due to actual changes in traffic conditions.
f. As explained below, if we either do not observe enough historical Waze data activity for some areas, or we observe high variability in the historical data, those areas are excluded from our reporting.

2. *Identification of geographic areas.* We query two types of areas (defined here as polygons):
   a. Countries: We query all 26 IDB borrowing member countries: Argentina, The Bahamas, Barbados, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, Uruguay, and Venezuela. The boundaries for each country are those used by OpenStreetMap.
   b. Metropolitan areas: It is very difficult to compare cities across countries, given that national definitions of cities tend not to be consistent across countries and rely on administrative, legal, or historical boundaries that may not necessarily reflect the functional and economic extent of cities (Dijkstra and Poelman 2012).[4] We use a consistent definition of metropolitan areas across countries that, instead of relying on administrative or legal country-specific definitions, is based on the following strategy:
      i. Following Dijkstra and Poelman (2012), we define an urban center as a human settlement with high population density and infrastructure of built environment created through urbanization processes.
      ii. Applying the methodology used by those authors requires having estimates of total population for Latin America and the Caribbean at 1 km^2 spatial resolution. To do this, we utilize data from the WorldPop database for 2020.[5]

[4] L. Dijkstra and H. Poelman (2012) "Cities in Europe: The New OECD-EC Definition." Regional Focus 1/2012, European Commission. Available at: https://ec.europa.eu/regional_policy/sources/docgener/focus/2012_01_city.pdf.

[5] F.R. Stevens, A.E. Gaughan, C. Linard, and A.J. Tatem (2015) "Disaggregating Census Data for Population Mapping Using Random Forests with Remotely-sensed and Ancillary Data." *PloS one* 10(2). Available at: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0107042

iii. We then use these gridded datasets as raster files to create urban centers as clusters of adjacent grids/pixels with over 1,500 inhabitants and with over 100,000 inhabitants, adapting the steps in Dijkstra and Poelman (2012).[6]

iv. Our initial list of clusters with over 100,000 inhabitants and country capitals has 292 candidate locations, which we then restrict to those urban centers with over 750,000 inhabitants, plus any country capital among the IDB member countries that does not have more than 750,000 inhabitants.

v. Once we apply the steps above and restrict the sample to urban centers with more than 750,000 inhabitants and country capitals, we arrive at a list of 78 metropolitan areas.

vi. We finally restrict the analysis to areas with enough Waze activity data and not too much variability historically (see details below), which implies that 19 countries and 64 metropolitan areas are included in the dashboard. As we report both daily and weekly measures, the restrictions are applied independently at each level of reporting. Tables 1 and 2 present the full list of metropolitan areas included in the dashboard for daily and weekly measures, respectively.

c. We calculate a (proxy) measure for traffic congestion using Waze data in each of the polygons at five- minute intervals (see below).

3. *Traffic Congestion Intensity (TCI)*

a. At every time interval i at which the data is analyzed and for every polygon, p, we calculate a measure of total jam length, L_{ip}, by adding the lengths of all jam lines[7] j in the polygon in that time interval:

$$JAM_{ip} = \sum L_{jip}.$$

b. The measure for a period t (in Version 2.0 defined as a full day[8]) adds up all the total jam lengths across all intervals in the period t:

$$TCI_{pt} = \sum JAM_{ip}.$$

c. This measure of *TCI* summarizes both the *extent* of jams in the street network of a polygon (e.g., a metro area) and their *duration*, because jam lengths are counted at each time interval i. For example, if in metropolitan area A and metropolitan area B the same 10 jam lines are formed in a day, each 150 meters long, we would have a measure of 1,500

[6] Dijkstra and Poelman (2012) define urban centers as contiguous (Rook contiguity) grid cells of 1 km^2 with a density of at least 1,500 inhabitants per km^2 and a minimum population of 50,000. Adapting their methodology, we apply the following steps. First, all cells with a population density of more than 1,500 inhabitants per km^2 are selected. Second, contiguous high-density cells are grouped. Third, to fill gaps and smooth sharp borders, the majority rule is applied iteratively. This means that if five or more of the cells surrounding a cell belong to a single high-density cluster, it is added to that high-density cluster. This is repeated until no more cells are added. Finally, we identify the single high-density cluster with a metropolitan area name using the latitude and longitude of the mayor's office or a major reference point of the city.

[7] We exclude from the analysis jam lines with a value of *traffic congestion level* in the Waze data equal to 5 (blocked) which refers to streets that are closed to traffic.

[8] Other calculations could involve partial days, such as traffic during the day versus traffic at night, or traffic during rush hours. Future versions of the dashboard will explore these possibilities.

meters jammed in both A and B during the day. However, if jams in A have a duration that is double the duration in B, the TCI for A would be double the TCI for B.

4. *Baseline period*
    a. The TCI is not particularly useful as a point-in-time measure, but it is useful to capture changes in jam intensity over time for a fixed-size polygon.
    b. In response to a mandatory lockdown or other restrictions and/or recommendations for "social distancing," we expect the TCI to decrease. As mentioned above, even if the TCI drops to zero (meaning there is no more congestion) it does not provide data on the remaining volume of vehicles on the roads (which must be circulating at "free-flow" speed, given there is no congestion). Hence the interpretation of TCI changes should be taken with caution, when trying to assess the impacts of government measures or recommendations.
    c. To calculate percentage changes, we need to select a reference point or baseline period against which to compare the TCI after the coronavirus outbreak.
    d. One option would be to consider the same weeks (to account for seasonality in traffic patterns) in the prior year (2019). However, we decided against this option in order to avoid potential confounding effects related to changes in Waze app penetration and Wazers' engagement, and/or related to metropolitan-area-wide or country-wide secular trends (e.g., changes in the macroeconomic context), which can affect traffic patterns.
    e. We also decided against using traffic data for January and February 2020 given the idiosyncratic characteristics of these months. For example, travel patterns and traffic during summer vacations and/or carnival during these two months in many countries in Latin America and the Caribbean are very different than the business-as-usual scenario.
    f. Therefore, the baseline period considered is the first week of March 2020 (March 2–8, 2020), as this was a week when traffic patterns were not expected to have been affected by holidays, and given that either no COVID-19 cases or a very small number of cases had materialized in the region up to that time. In addition, no restrictions or recommendations had been issued to the population. (See Table 3 for details on the timing of coronavirus milestones in Latin America and the Caribbean.)

5. *Day-of-the-Week effects*
    a. The data shows there are systematic differences in TCI patterns across the days of the week (see Figure 1).
    b. To control for these systematic differences, we use only day-of-the-week pairs when we calculate TCI changes. That is, all Mondays are compared to a baseline Monday, all Tuesdays to a Baseline Tuesday, etc.

6. *Change in Traffic Congestion Intensity* (ΔTCI)
    a. We evaluate changes in the TCI in polygon p in period t by simply calculating the percentage change in the TCI with respect to the corresponding day-of the-week baseline period:

$$\Delta\mathrm{TCI}_{pdt_1} = \left(\frac{TCI_{pdt_1}}{TCI_{pdt_0}} - 1\right) \times 100,$$

where:

TCI = Traffic Congestion Intensity
p= Polygon (metropolitan area or country)
d= Day of the week
t_1= Evaluation period
t_0= Baseline period

7. *Metropolitan areas and countries reported*
   a. For some metropolitan areas (and countries) the historical data shows that either there is not enough Waze daily activity and/or there is too much variability, for us to deem the TCI measure to be a reliable measure of traffic congestion changes in that area. We do not report TCI changes in these areas, as shown in Tables 1 and 2, for daily and weekly analyses, respectively.
   b. We apply two criteria (both need to be satisfied) for a polygon to be included in our analysis (independently at the daily and the weekly level):
      i. Historical variability. Using data for 2019, we obtain (both at daily and weekly levels) the average and standard deviation of the TCI. We then calculate the *coefficient of variation* (standard deviation/average) of the daily and weekly TCI. We only consider in the analysis those polygons (metro area, country) with a coefficient of variation < 0.5.
      ii. Historical Waze data activity. Using data for 2019, we obtain the daily average of the TCI for the polygon (for the weekly data we also express it as a daily average dividing it by 7) and take the ratio of this average to the length of the road network in the same polygon, according to Open Street Map. (We only consider Roads in the Open Street Map classification.) We only include in our analysis those polygons with a ratio TCI/OSM length > 0.10.

8. *Country-level* ΔTCI
   a. As we obtain country-level values of the TCI from country-wide queries, this implies that for different countries the metropolitan areas within those countries for which we present information may explain a larger or smaller share of the overall country TCI. Thus, an average of the metropolitan area indexes could potentially diverge from the country-wide index. Tables 1 and 2 present data on the share of the country's TCI explained by each metropolitan area within a country, on average, during 2019.
   b. Conceptually, a (potentially weighted) average of metropolitan-area-level TCI is different from the country-wide measure because with any fixed-weight scheme for obtaining the average, changes over time in the relative importance of the TCI in a metropolitan area (compared to the other metropolitan areas in the country) are not captured. For this reason, and due to its simplicity of calculation, we opt for calculating country-level measures using full country polygon queries.

- **Air Quality**

1. *Nitrogen dioxide*
    a. Nitrogen dioxide (NO_2) is a gaseous air pollutant and is one of a group of related gases called **nitrogen** oxides, or NOx. This is a pollutant that has a direct connection to fossil fuel emissions. Most airborne NO_2, comes from high temperature combustion of emission sources of human origin such as coal, oil, gas or diesel. The largest source of nitrogen dioxide emissions are cars, trucks, and buses, followed by power plants, diesel-powered heavy construction equipment and other movable engines.
    b. According to health departments the main effect of breathing in high levels of nitrogen dioxide is the increased likelihood of respiratory problems. Nitrogen dioxide inflames the lining of the lungs, and it can reduce immunity to lung infections. This can cause problems such as wheezing, coughing, colds, flu and bronchitis. Increased levels of nitrogen dioxide can have significant impacts on people with asthma because it can cause more frequent and more intense attacks. Children with asthma and older people with heart disease are most at risk. All these can lead to increases in morbidity and mortality.
    c. Since NO_2 is created when burning fossil fuels, it is directly correlated to changes in human activity. Montgomery and Holloway (2018) find a positive relationship between the increase in gross urban product and NO_2 vertical column densities from NASA's Aura satellite.[9] Moreover, reductions in NO_2 levels have been correlated not only with higher enforcement of environmental standards but also with lower economic activity from an economic recession as in Castellanos and Boersma (2012).[10]
    d. So, we follow NO_2 concentrations during the coronavirus outbreak in order to track not only the extent to which "social distancing" restrictions are having an impact on one of the pollutants that contribute to lower air quality, but also as a possible *proxy* for changes in economic activity.

2. *Satellite derived NO_2*
    a. Satellite observations of NO_2 tropospheric columns are useful for observing trends in NO_2 concentrations and inferring surface emissions on regional scales. Satellite observations cover regional areas and provide consistent time series of NO_2 concentrations.
    b. We present trends in NO_2 concentrations over LAC cities measured with the [TROPOspheric Monitoring Instrument (TROPOMI)] starting in March 2020. We use the tropospheric vertical column density observed under "cloud free" conditions and over a high-quality assurance value of 0.75.
    c. The raster images show nitrogen dioxide concentrations and we use measures at 10-day periods since concentrations vary from day to day due to changes in weather conditions. By combining data for 10 days we average out the meteorological variability so we can

[9] Montgomery, A. and T. Holloway (2018). Assessing the relationship between satellite-derived NO2 and economic growth over the 100 most populous global cities, J. Appl. Rem.Sens.,12(4), https://doi.org/10.1117/1.JRS.12.042607.

[10] Castellanos, P. and Boersma (2012). Reductions in nitrogen oxides over Europe driven by environmental policy and economic recession. Sci Rep 2, 265. https://doi.org/10.1038/srep00265.

see the impact of changes due to human activity. We focus on 10-day periods compared to March 1-10, 2020, a similar baseline used in the TCI analysis.

3. *Metropolitan areas and methodology*
    a. We processed satellite data for all LAC cities but we present a sample of cities in the region with varying degrees of lockdown measures in place during the 3rd week of March. We chose Buenos Aires, Bogotá, Medellín, Quito, Guayaquil and Lima for countries with a total lockdown policy and compared them with Sao Paulo, Rio de Janeiro, Santiago de Chile, Ciudad de México and Kingston. The last set of cities did not have total lockdowns in place but rather some partial social distancing measures.
    b. We present the maps for each city-period, with each pixel having a size of 3.3x3.3 kilometers near the equator. Since the TROPOMI instrument has a spatial resolution of 3.5x7 km^2 we interpolated the data for each day using a weighted inverse distance methodology with up to 6 neighbors searching for computational ease.
    c. The bar graph showing the percent change in NO_2 concentrations was created by weight averaging the value of each pixel by the total amount of population in 2020 according to the WorldPop data, and up to 30 kms away from the city center. We then created a simple percent change of the values before and after for each city.

V. Code

In an effort to help researchers replicate and expand analysis, when applicable all code used is available in the IDB's Code for Development GitHub repository under Coronavirus Dashboard. This repository reflects the code being used in the most current version of the dashboard.

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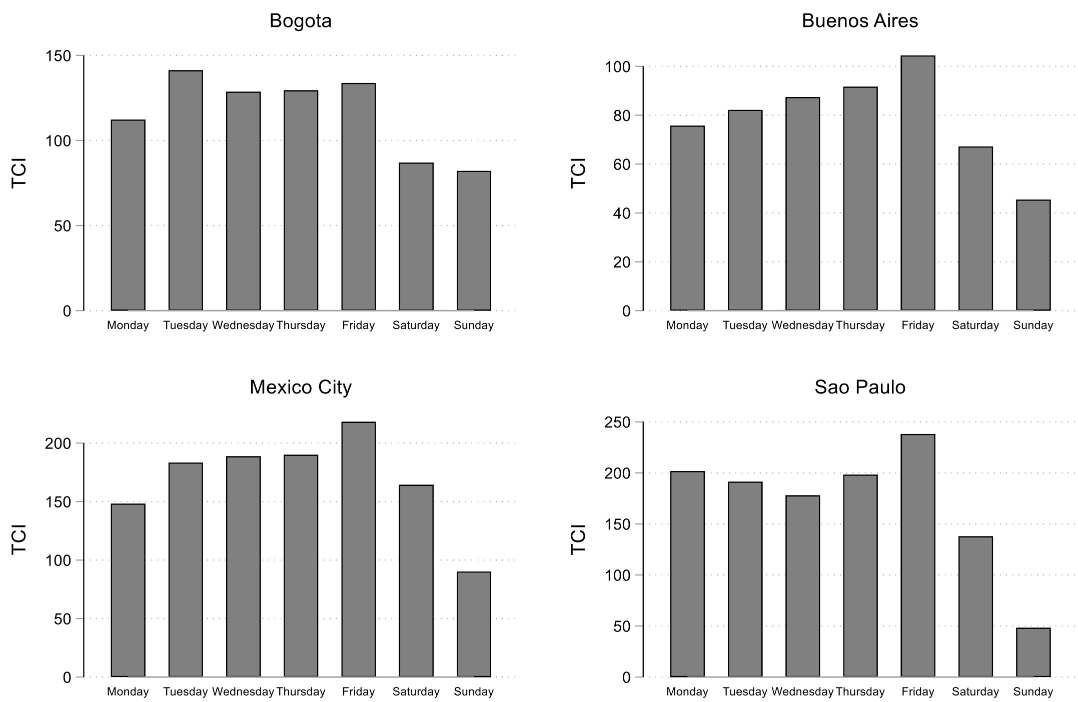
Figures and Tables

Figure 1. Baseline Period Traffic Congestion Intensity by Day of the Week, Selected Cities



Note: Traffic congestion intensity is measured in thousands of kilometers.

Table 1. Daily Measures Used to Select Countries and Areas Reported (2019)

Country	CV	TCI/ OSM Ratio	Metropolitan area	CV	TCI/ OSM Ratio	Share TCI (%)
Argentina	0.28	0.26	Buenos Aires	0.33	2.67	41.11
			Córdoba	0.36	1.07	2.74
			Mendoza*	0.51*	0.41	0.64
			Rosario	0.34	0.46	0.77
Bahamas*	0.45	0.04*	New Providence*	0.60*	0.07*	25.79
Barbados	0.43	0.18	Bridgetown*	0.65*	0.24	69.11
Belize*	0.66*	0.05*	Belmopan*	1.91*	0.01*	0.29
Bolivia*	0.32	0.03*	Cochabamba*	0.39	0.02*	1.07
			La Paz*	0.38	0.05*	2.73
			Santa Cruz de la Sierra	0.38	0.71	70.95
Brasil	0.29	0.58	Belo Horizonte	0.37	3.60	2.41
			Belém	0.33	4.34	1.05
			Brasília	0.34	1.96	0.95
			Campinas	0.41	1.52	0.80
			Curitiba	0.40	3.23	1.66
			Fortaleza*	-	-	-
			Goiânia	0.38	1.60	0.92
			João Pessoa	0.37	2.01	0.42
			Maceió	0.35	4.24	0.62
			Manaus	0.36	4.30	1.11
			Natal	0.32	3.55	1.68
			Porto Alegre	0.40	3.21	1.87
			Recife	0.32	4.63	2.15
			Rio de Janeiro	0.35	4.79	5.79
			Salvador	0.40	5.75	1.67
			Santos	0.35	3.91	0.81
			São José dos Campos	0.34	1.99	0.33
			São Luís	0.36	2.52	0.65
			São Paulo	0.38	5.84	13.18
			Teresina	0.36	1.82	0.43
			Vitória	0.38	2.30	0.72
Chile	0.23	1.04	Santiago	0.46	4.74	31.40
Colombia	0.22	1.61	Barranquilla	0.32	4.48	3.82
			Bogotá	0.29	12.98	35.55
			Bucaramanga	0.35	2.23	1.21
			Cali	0.33	4.92	5.21
			Cartagena de Indias	0.28	3.62	1.51
			Cúcuta	0.37	0.42	0.25
			Medellín	0.35	6.40	7.61
			Pereira	0.36	4.12	1.26
Costa Rica	0.21	2.00	San José	0.35	7.02	36.92
Ecuador	0.25	0.39	Guayaquil	0.37	1.92	22.06
			Quito	0.33	4.23	53.67
El Salvador	0.35	1.13	San Salvador	0.40	6.04	54.90
Guatemala	0.26	1.10	Ciudad de Guatemala	0.33	6.11	60.67
Guyana*	0.84*	0.01*	Georgetown*	0.66*	0.06*	38.10
Haiti*	0.84*	0.02*	Port-au-Prince*	0.63*	0.07*	40.89
Honduras	0.31	0.21	Tegucigalpa	0.47	1.00	25.40
Jamaica	0.25	0.12	Kingston	0.49	0.40	25.86

México	0.31	0.84	Aguascalientes	0.35	1.34	0.49
			Ciudad de México	0.29	5.23	24.51
			Guadalajara	0.28	3.67	4.96
			Juárez*	0.54*	1.13	0.76
			León	0.36	1.74	0.90
			Monterrey	0.38	2.32	3.57
			Mérida	0.32	1.36	0.72
			Puebla	0.25	2.35	2.07
			Querétaro	0.31	2.81	1.33
			San Luis Potosí	0.40	2.14	0.85
			Tijuana*	0.54*	2.61	1.55
			Toluca	0.31	2.64	1.90
			Torreón	0.49	0.70	0.37
Nicaragua	0.27	0.29	Managua	0.36	1.08	32.31
Panama	0.27	1.62	Ciudad de Panamá	0.43	8.04	57.09
Paraguay	0.45	0.12	Asuncion*	0.50*	1.46	79.66
Peru	0.20	0.52	Arequipa	0.33	2.02	3.18
			Lima	0.24	4.81	65.09
República Dominicana	0.30	1.15	Santiago de los Caballeros	0.35	2.77	13.43
			Santo Domingo	0.36	4.75	73.26
Suriname*	0.47	0.08*	Paramaribo*	0.51*	0.29	75.19
Trinidad and Tobago	0.44	1.58	Port of Spain*	0.58*	4.96	30.70
			San Fernando*	0.58*	2.64	15.06
Uruguay	0.32	0.52	Montevideo	0.20	4.32	65.69
Venezuela*	0.60*	0.04*	Barquisimeto*	5.00*	0.03*	1.19
			Caracas*	0.76*	1.33	76.57
			Maracaibo*	0.82*	0.00*	0.23
			Maracay*	0.73*	0.05*	2.49
			Valencia*	0.77*	0.06*	3.50

Notes:

i. CV refers to coefficient of variation; TCI/OSM ratio refers to the average ratio of the daily TCI to the Open Street Map road network length; Share TCI refers to the average share of the daily TCI of a metropolitan area to the country’s TCI. All measures use 2019 Waze data.

ii. Sum of TCI shares within a country may not add up to 100 percent, as country-level traffic congestion intensity is based on data for the whole country.

iii. * Indicates countries and areas not reported in the dashboard. Only countries and metropolitan areas with TCI CV < 0.50 and TCI/OSM ratio > 0.10 are reported. The * next to a number indicates the criterion that is binding.

Table 2. Weekly Measures Used to Select Countries and Areas Reported (2019)

Country	CV	TCI/ OSM Ratio	Metropolitan area	CV	TCI/ OSM Ratio	Share TCI (%)
Argentina	0.26	0.26	Buenos Aires	0.22	2.62	41.11
			Córdoba	0.35	1.05	2.74
			Mendoza	0.36	0.41	0.64
			Rosario	0.24	0.45	0.77
Bahamas*	0.32	0.04*	New Providence*	0.36	0.06*	25.79
Barbados	0.26	0.18	Bridgetown	0.32	0.24	69.11
Belize*	0.51*	0.05*	Belmopan*	0.68*	0.01*	0.30
Bolivia*	0.31	0.03*	Cochabamba*	0.24	0.02*	1.07
			La Paz*	0.28	0.05*	2.73
			Santa Cruz de la Sierra	0.36	0.70	70.95
Brasil	0.22	0.58	Belo Horizonte	0.24	3.54	2.37
			Belém	0.24	4.27	1.03
			Brasília	0.23	1.93	0.94
			Campinas	0.23	1.50	0.79
			Curitiba	0.24	3.18	1.63
			Fortaleza*	-	-	-
			Goiânia	0.22	1.58	0.90
			João Pessoa	0.21	1.98	0.42
			Maceió	0.18	4.18	0.61
			Manaus	0.20	4.23	1.09
			Natal	0.21	3.49	1.65
			Porto Alegre	0.23	3.16	1.84
			Recife	0.19	4.55	2.12
			Rio de Janeiro	0.21	4.71	5.69
			Salvador	0.20	5.66	1.64
			Santos	0.27	3.85	0.80
			São José dos Campos	0.22	1.96	0.32
			São Luís	0.25	2.48	0.64
			São Paulo	0.23	5.74	12.96
			Teresina	0.25	1.79	0.42
			Vitória	0.20	2.26	0.71
Chile	0.15	1.03	Santiago	0.28	4.66	31.40
Colombia	0.19	1.58	Barranquilla	0.19	4.41	3.82
			Bogotá	0.22	12.77	35.55
			Bucaramanga	0.25	2.19	1.21
			Cali	0.21	4.84	5.21
			Cartagena de Indias	0.21	3.56	1.51
			Cúcuta	0.30	0.42	0.25
			Medellín	0.24	6.30	7.61
			Pereira	0.29	4.06	1.26
Costa Rica	0.15	1.97	San José	0.24	6.91	36.92
Ecuador	0.18	0.38	Guayaquil	0.22	1.89	22.06
			Quito	0.21	4.16	53.67
El Salvador	0.31	1.11	San Salvador	0.24	5.94	54.90
Guatemala	0.20	1.08	Ciudad de Guatemala	0.22	6.01	60.67
Guyana*	0.43	0.01*	Georgetown*	0.37	0.05*	38.10
Haiti*	0.65*	0.02*	Port-au-Prince*	0.55*	0.07*	40.89
Honduras	0.26	0.20	Tegucigalpa	0.34	0.98	25.40
Jamaica	0.18	0.12	Kingston	0.27	0.40	25.86

México	0.27	0.84	Aguascalientes	0.29	1.32	0.48
			Ciudad de México	0.20	5.14	24.11
			Guadalajara	0.21	3.61	4.87
			Juárez*	0.51*	1.12	0.75
			León	0.26	1.71	0.88
			Monterrey	0.25	2.28	3.52
			Mérida	0.22	1.34	0.70
			Puebla	0.19	2.31	2.04
			Querétaro	0.21	2.77	1.31
			San Luis Potosí	0.29	2.10	0.84
			Tijuana*	0.51*	2.57	1.52
			Toluca	0.22	2.60	1.87
			Torreón	0.44	0.69	0.37
Nicaragua	0.24	0.29	Managua	0.23	1.06	32.31
Panama	0.17	1.59	Ciudad de Panamá	0.20	7.91	57.09
Paraguay	0.40	0.12	Asuncion	0.42	1.43	79.66
Peru	0.17	0.51	Arequipa	0.23	1.99	3.18
	0.17	0.51	Lima	0.16	4.73	65.09
República Dominicana	0.21	1.14	Santiago de los Caballeros	0.20	2.72	13.43
			Santo Domingo	0.23	4.68	73.26
Suriname*	0.35	0.08*	Paramaribo	0.44	0.29	75.19
Trinidad and Tobago	0.26	1.55	Port of Spain	0.29	4.88	30.70
			San Fernando	0.31	2.59	15.06
Uruguay	0.30	0.51	Montevideo	0.21	4.25	65.69
Venezuela*	0.45	0.04*	Barquisimeto*	2.08*	0.03*	1.19
			Caracas*	0.58*	1.31	76.57
			Maracaibo*	0.49	0.00*	0.23
			Maracay*	0.46	0.05*	2.49
			Valencia*	0.44	0.06*	3.50

Notes:

i. CV refers to coefficient of variation; TCI/OSM ratio refers to the average ratio of the weekly TCI (divided by 7) to the Open Street Map road network length; Share TCI refers to the average share of the weekly TCI of a metropolitan area to the country's TCI. All measures use 2019 Waze data.

ii. Sum of TCI shares within a country may not add up to 100 percent, as country-level traffic congestion intensity is based on data for the whole country.

iii. * Indicates countries and areas not reported in the dashboard. Only countries and metropolitan areas with TCI CV < 0.50 and TCI/OSM ratio > 0.10 are reported. The * next to a number indicates the criterion that is binding.

Table 3. Timing of Coronavirus Detection and Social Distancing Measures Adopted in Latin American and the Caribbean

Country	Date of Total Lockdown	Date of First Social Distancing Measures	Current Type of Lockdown	Date of First Confirmed COVID-19 Case
Argentina	20-Mar	14-Mar	Total	3-Mar
Bahamas, The	24-Mar	19-Mar	Total	16-Mar
Barbados		16-Mar	Partial	17-Mar
Belize		20-Mar	Partial	23-Mar
Bolivia	22-Mar	12-Mar	Total	11-Mar
Brazil		19-Mar	Partial	26-Feb
Chile		15-Mar	Partial	3-Mar
Colombia	2-Mar	12-Mar	Total	6-Mar
Costa Rica		12-Mar	Partial	6-Mar
Dominican Republic		16-Mar	Partial	1-Mar
Ecuador	22--Mar	11-Mar	Total	1-Mar
El Salvador	21-Mar	11-Mar	Total	19-Mar
Guatemala		16-Mar	Partial	14-Mar
Guyana		16-Mar	Partial	12-Mar
Haiti		19-Mar	Partial	11-Mar
Honduras	20-Mar	12-Mar	Total	11-Mar
Jamaica		13-Mar	Partial	11-Mar
Mexico		20-Mar	Partial	28-Feb
Nicaragua			None	19-Mar
Panama	25-Mar	16-Mar	Total	10-Mar
Paraguay	20-Mar	9-Mar	Total	8-Mar
Peru	16-Mar	15-Mar	Total	6-Mar
Suriname		14-Mar	Partial	14-Mar
Trinidad and Tobago		13-Mar	Partial	12-Mar
Uruguay		13-Mar	Partial	14-Mar
Venezuela	17-Mar	12-Mar	Total	14-Mar

Note: Information includes all measures announced as of April 27, 2020.