TAPTAP COVID-19 REPORT
Geospatial Analysis

COUNTRY: SPAIN
DATE: FEBRUARY 2020 - APRIL 2020

TAPTAP

ABOUT TAPTAP

TAPTAP Digital is a marketing and advertising technology company founded in 2010 that services global markets in more than 80 countries. Through its proprietary platform Sonata, TAPTAP offers solutions based in geospatial and audience intelligence applied to advanced audience profiling, dynamic advertising activation and measurement of online and offline results.

Sonata Location Intelligence (Sonata Li) is the system within the Sonata platform that empowers multivariate analysis of static and dynamic data sources in real time to generate audience indexes and indicators to identify behavior at the geographic level.

Sonata operates by integrating first and third party anonymous data such as mobile phone navigation, geo positioning data, census data, statistical data and other dynamic sources to perform a holistic and comprehensive geospatial analysis in real time. TAPTAP and its collaborators provide independent analysis based on non-identifying data that has been provided and verified within the current European Community legal framework based on consent.

STUDY OVERVIEW

In the current context of global confinement, TAPTAP has developed an initial study to understand the relationship between mobility and the evolution of the pandemic.

For this study TAPTAP has collaborated with big data and artificial intelligence experts at the Carlos III University of Madrid and companies Predicio and Tamoco who provide high frequency and precision location data.

This first report focuses on Spain from the time mobility restrictions were announced due to COVID19 until April 2020. We developed multivariable indexes that analyze vulnerability of each province according to mobility, population composition and points of interest like hospitals, pharmacies and grocery stores. Where the cause and effect relationship is not always immediately apparent or direct, it is necessary to conduct a continuous analysis over time. We will, therefore, publish an additional report in the coming weeks that provides greater continuity to the analysis.

We think it is very relevant to understand the link between the return to commercial and consumer activity and the evolution of the pandemic in the coming weeks. The reduction of confinement will therefore be a cause for additional monitoring as it could lead to additional outbreaks which likewise affect economic recovery.

ABOUT THE DATA

Privacy:

Location and mobility data has been provided by the Sonata technology owned by TAPTAP Digital SL. Sonata is an advanced marketing platform that provides access to anonymized mobility data which is collected with due consent through the legal framework provided by the General Data Protection Regulation (GDPR). The data is collected from users who have chosen to provide access to their location data and have undergone processes that allow anonymization and prevent data from being linked to an individual. Precise location data has also been supplied by providers like Predicio or Tamoco who participated in this study. The necessary measures have been taken in every case to ensure that the data processed for the implementation of this report is anonymized. Read more about the data and methodology.

Devices for this representative sample were active for part of February, during the entire month of March and part of April 2020. The resulting sample is roughly 2% of the total population of Spain which represents approximately 300 million data points for the duration of the 6 week study, and is highly representative of the national population.

GENERAL ANALYSIS

The multivariable indexes presented show the evolution, behavior and trends of several key indicators and the relationship between them with respect to the pandemic. They provide a composite image for the analysis of each geographic area, population group or trend which will provide valuable information for the staggered reactivation of commercial activity.

The results of the study are presented in 4 sections:

1. COVID-19 official data around cases, hospitalizations, deaths, UCI patients and recovered patients.
2. *User Behavior (Mobility)* Indicators of changes in population habits in the context of COVID19.
3. *Demographics and social variables*: identification of the risk of each territory and natural vulnerability rates depending on the composition of its inhabitants.
4. *Geographic Context*: Points and areas of interest with high demand or saturation that can expose the population or condition their habits. User density by area and by point of interest.

POST COVID19 CONSUMPTION

We are at an unprecedented moment, where there is no roadmap, presenting a very complex dilemma for many institutions. Ensuring the personal health of citizens means the destruction of the economy, employment and economic engine of any country, production and consumption. For this purpose, TAPTAP, as an ally of large brands and institutions for the execution of data-driven advertising communication campaigns, understands that indicators in behavior, both physically and digitally of consumers, as well as those of consumption, are key to being able to understand the relationship of the gradual reactivation of the economy with respect to future pandemic developments. Likewise, we understand that there will be a new post-COVID19 consumer, with altered shopping habits. Therefore, as we produce complex multivariate analyses, which allow us to correlate different data sources, we will enrich the vision of the consumer, their habits and their relationship with brands and institutions with the goal of predicting consumer behavior in relation to the current and future situation.

CONCLUSIONS

1. Confinement measures have succeeded in reducing overall mobility across every province in Spain roughly 80%; however, to properly quantify reduction in mobility, a baseline must be calculated and incorporated into the mobility analysis. A baseline is likewise necessary to create quantitative correlations between reduced mobility and COVID19 indicators, economic changes and policy changes - especially as mobility restrictions relax.

Takeaway: While organic mobility is different per province, mobility generally dropped from a baseline of 25km per day to 5km per day, nationally.

2. Each COVID public policy announcement has a measurable effect on mobility. The baseline can help us: 1) Understand which policies have the greatest effects 2) Observe the time it takes for the effect to be seen

Takeaway: Daily traffic continued to decline for 5 days after the initial state of alarm. The restriction of all non-essential activity started to significantly affect mobility about 5 days later, and, as expected, had the greatest impact on mobility.

3. Quarantine policies have a measurable effect on COVID cases, hospitalizations and deaths.

Takeaway: The data indicates that quarantine policies require about 15 days to effect the reduction of total new cases and new deaths

4. Analyzing indicators affecting the evolution of the virus or of the risk in a particular geographic area in an isolated manner could lead to incorrect conclusions or biased assessments. Multivariable indexes produce a more comprehensive analysis. According to population density, Madrid and Bareclona represent the most risk of contagion in Spain; however, introducing other variables like density of at risk population, especially relative to the capacity for coverage of critical points of interest (Hospitals, Pharmacies, Supermarkets), we recognize that unexpected provinces may require additional protection measures or mobility restrictions.

Takeaways
- *Castellón, Cantabria and Guipúzcoa have the highest concentration of at risk populations in proportion to total population.*
- *Toledo, Segovia, Salamanca or Navarra have less hospital coverage per vulnerable population.*

5. Using a baseline[1] to perform a hyperlocal analysis, or observing the foot traffic in the immediate radius of a particular POI, will help us understand physical consumption patterns triggered by the new normal. Understanding consumption patterns will help businesses and brands better communicate with the new consumer. Likewise, monitoring changes in digital navigation, not only across content categories, but also with regard to other indicators like network connection informs consumption patterns.

Takeaway: Internet traffic has jumped by 400% and the fastest growing categories are entertainment and online shopping. Online consumption in the confinement is roughly the same on every day of the week, but Wednesday and Thursday see slightly lower consumption.

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1. Baseline. The baseline is the average value of the mobility in the 15 - 20 days prior to the lockdown.

Geographic Analysis - Dynamic Data

POPULATION MOBILITY

Fig. 1. Week over week mobility variation in March 2020, Per Province. *Source: Sonata LI (TAPTAP) | UC3M | Predicio*
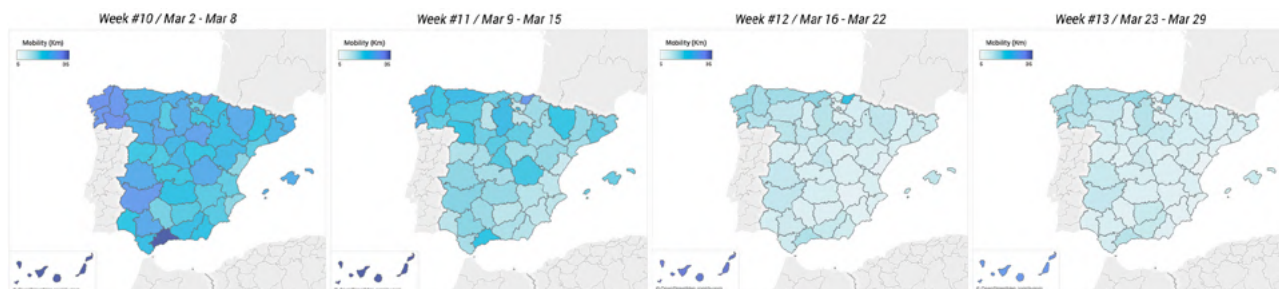
Analysis of the average mobility per user and province (daily KMs). Certain provinces are more dispersed than others, which naturally requires more mobility. However, as the confinement evolves, mobility among all provinces homogenizes, with minimal movement everywhere.

Fig. 2. Variation of national mobility, Spain. *Source: Sonata LI (TAPTAP) | UC3M | Predicio*
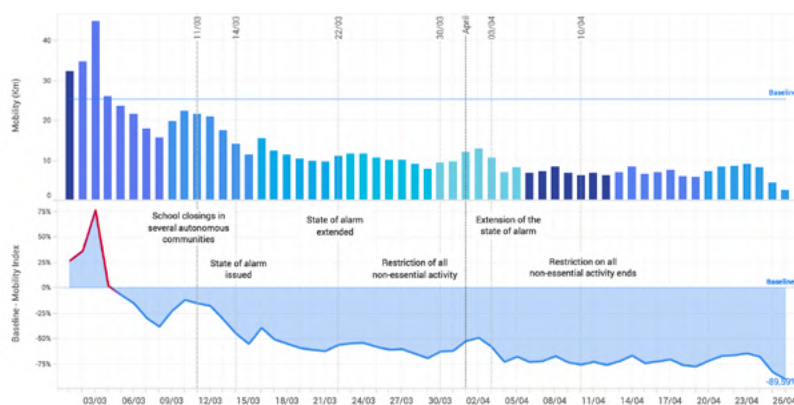
In this graph we can observe the mobility changes relative to a baseline of pre-COVID19 data. A baseline is a benchmark figure used to measure standard movement patterns allowing us to identify changes and patterns.

In this case, the baseline is the average value of the mobility in the 15 - 20 days prior to the lockdown.

Fig. 3. Variation of national mobility. *Source: Sonata LI (TAPTAP) | UC3M | Predicio*
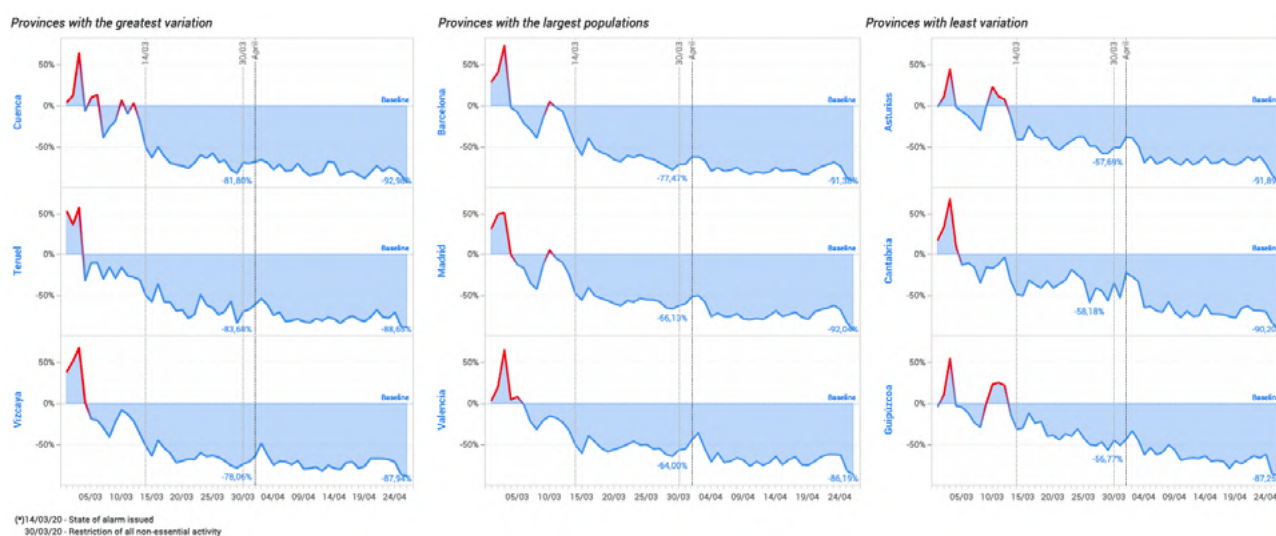
Average mobility rates change from 25 km per day to only 5 km per day with respect to the baseline, which is an 80% reduction in mobility.

Each policy announcement is followed by a decrease in weekly mobility even though patterns in all provinces are slightly different. Cuenca and Teruel are the areas with the least reduction in mobility where Asturias and Cantabria are the provinces with most variation in mobility.

OTHER INDICATORS

Variation in weekend versus weekday mobility

Fig. 4. National mobility variation between weeks 10 and 13, Spain. *Source: Sonata LI (TAPTAP) | UC3M | Predicio*
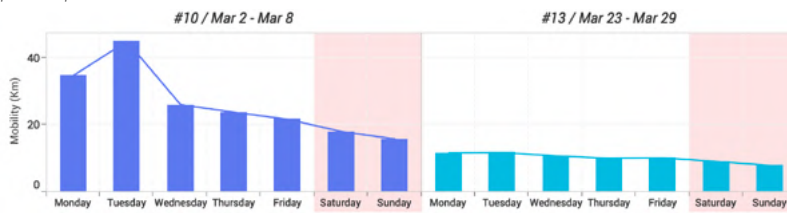
During a typical week, user mobility on weekdays is roughly double that on weekends. In confinement, **however, there is a minimal percentage difference between weekends and weekdays (10-15%)**, and overall distance travelled falls below 10KM per day.

Fig. 5. Changes in digital traffic density per zip code and daypart between weeks 10 and 13. Madrid, Spain. *Source: Sonata LI (TAPTAP)*
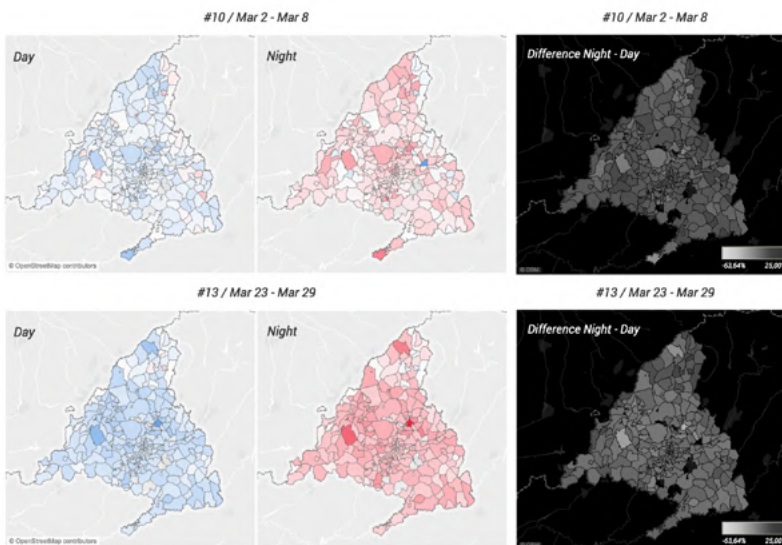
Using Madrid as an example, the maps show the differences in traffic density per zip code between day and night as indicated by mobile device location.

The blue graph shows the density of users during the day, whereas the red graph shows total density at night, per zip code.

The negative (greyscale) graph shows the sum difference between day and night. Lighter areas indicate less change from day to night, darker areas more.

Week 10 shows a greater disparity between day and night, especially in peripheral zip codes, which are usually more commercial than residential.

In week 13, when confinement is widespread, the traffic per each zip code between day and night are largely the same - as is indicated by the homogeneous colors in the negative graph.

Fig. 6. COVID-19 Mobility and hospitalizations, Spain. *Source: Sonata LI (TAPTAP) | Ministerio de Sanidad | UC3M | Predicio | Tamoco*
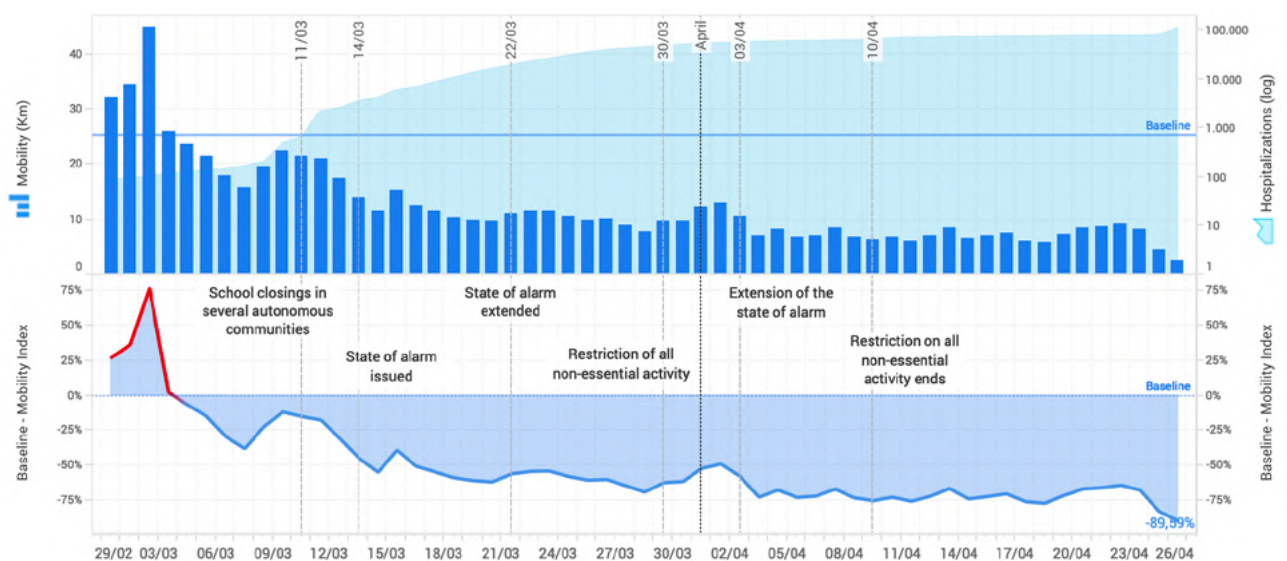
We use a logarithmic scale (a way to represent exponential increases in data without skewing results to the outliers) to measure the rate of mobility against the rate of hospitalizations. The multivariable analysis determines that the rate of hospitalizations starts to plateau about 15 - 20 days after the quarantine began, indicating that it takes about this long to see benefits from the policy.

Each policy announcement is followed by a decrease in mobility which represents a correlation between mobility and therefore hospitalizations.

Geographic & Population Analysis

Analysis Vulnerable Demographics

The following four graphs show the distribution of the population by total volume, and then by age bracket.

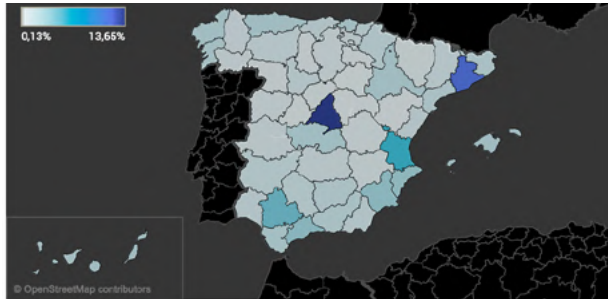**Fig. 7. Distribution of the total population, Per Province**

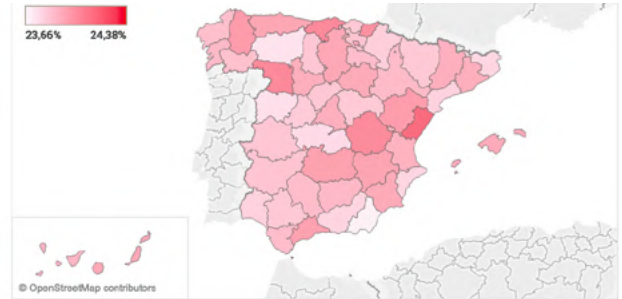**Fig. 8. Distribution of the vulnerable population, Per Province**

Fig. 9. Distribution of youth population, Per Province
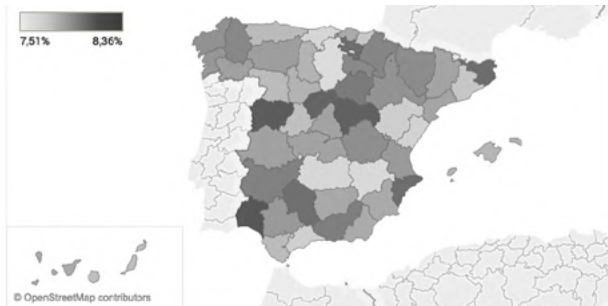*Source: Sonata LI (TAPTAP) | INE*

Fig. 10. Distribution of the adult population, Per Province

Figure 8 shows the classification of each province per proportion of vulnerable population (ages 65+). Even though their total population is low, Castellón, Cantabria and Guipúzcoa have a higher percentage of vulnerable population and therefore represent a higher risk.

Fig. 11. Index of population type by age group and total volume. *Source: Sonata LI (TAPTAP) | INE*
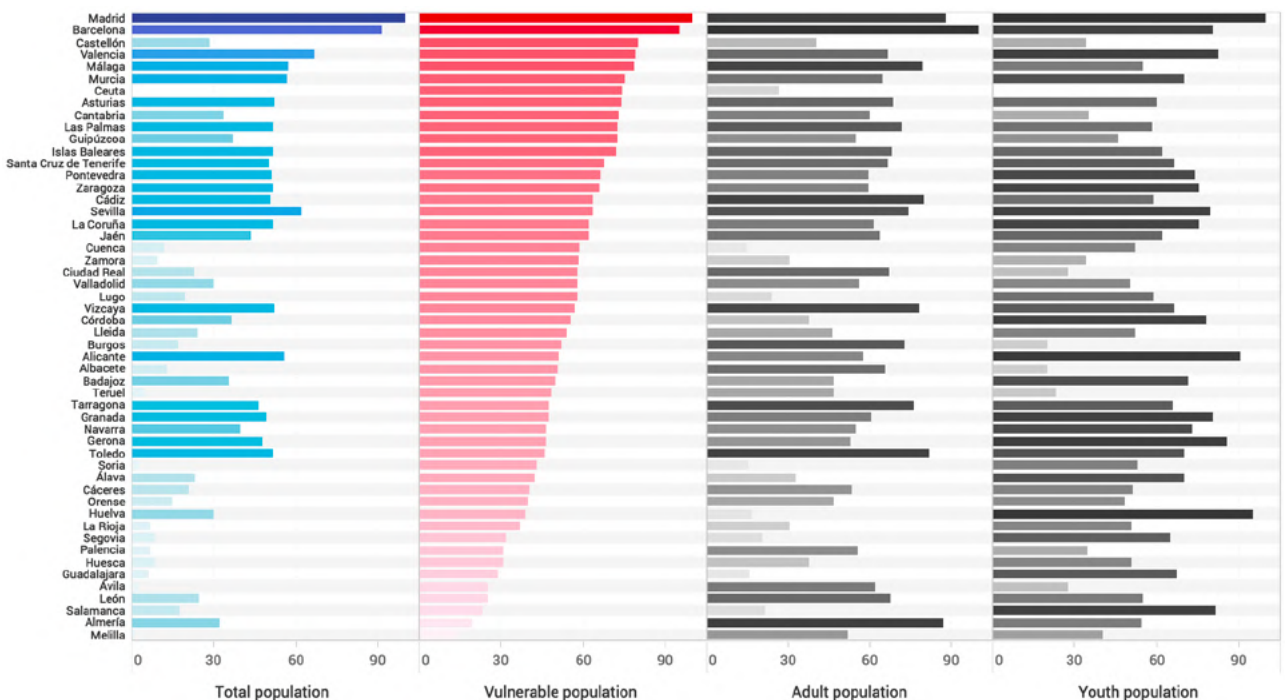

As is represented in figures 7-10, using multivariable indices allows us to analyze the data against more than one factor. Figure 11 for example shows the data incorporating both the total volume of the vulnerable population, but also the proportion (%) of vulnerable population with respect to the total. Madrid, Barcelona and Castellon still represent a risk for the vulnerable population, but with a multivariable index, Valencia and Málaga move to the top of the list.

CONTEXTUAL ANALYSIS: POINT OF INTEREST COVERAGE

Incorporating mobility data on the density of different points of interest (POIs) helps us see that areas with fewer POIs require more mobility and that areas with higher user saturation by POI can generate an increased risk of exposure to the virus.

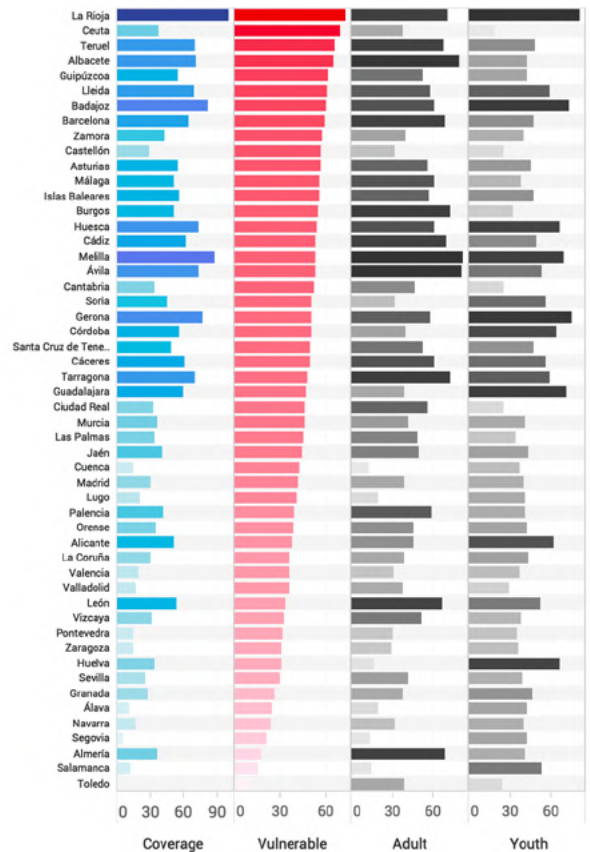### Hospital and health services coverage per population density and age

Fig.12. Index of hospital coverage per total population density. Source: Sonata LI (TAPTAP) | INE
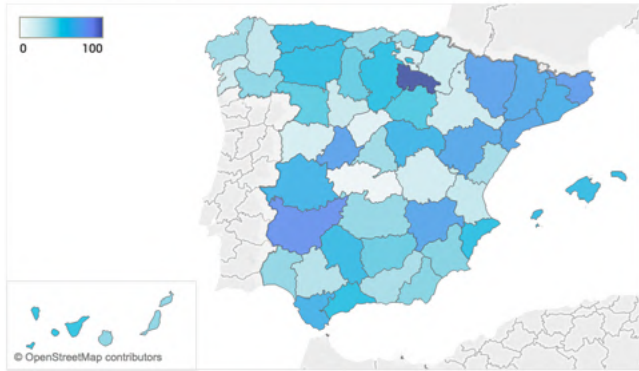
For example, the number of hospitals per region is not necessarily a significant figure in isolation. A more telling ratio is the volume of hospitals, or any POI, relative to the fixed volume of population it serves, or coverage of the POI. For example, in figure 13, we measure hospital coverage per each age group. Rioja, Teruel and Albacete have sufficient hospital coverage with respect to total population density, but because their vulnerable population index is not high, they may have an advantage. Alternatively, Toledo, Segovia Salamanca and Navarra may be at a disadvantage according to the indexes.

NOTE: Neither number of hospital beds nor ad hoc hospitals in centers like IFEMA were taken into consideration for these coverage rates

Fig. 14. Hyperlocal Analysis: Traffic in Severo Ochoa Hospital in Leganes (Madrid). Source: Sonata LI (TAPTAP) | UC3M | Predicio


Geo-level analysis can be studied in aggregate form per territory, but also at a hyperlocal level.

In the graph, individualized data by POI (Hospital Severo Ochoa in Leganes) allows us to analyze the user traffic in the area and compare it with its reference mean, or Baseline.

Fig. 13. Index of hospital coverage per population volume and age bracket. Source: Sonata LI (TAPTAP) | INE

Pharmacy coverage per population density

Fig. 15. Index of pharmacy coverage per population density. Source: Sonata LI (TAPTAP) | INE
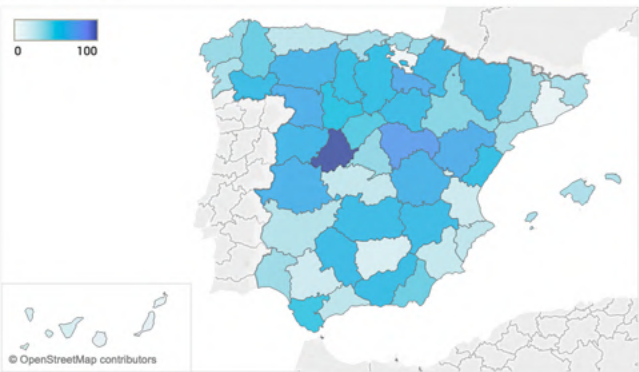

Barcelona and Madrid lead in population density in Spain, but have less pharmaceutical coverage per person. In contrast, Avila, Zamora and Castellón have higher pharmaceutical coverage rates relative to the vulnerable population index, so may be better equipped to meet demand.

Fig. 17. Hyperlocal Analysis: Traffic in a residential pharmacy in Madrid, Spain. Source: Sonata LI (TAPTAP) | UC3M | Predicio

The hyperlocal analysis of the pharmacy shows that while foot traffic drops below the baseline after the state of alarm is issued, it experiences consistent increases and decreases in traffic, not a continuous drop. This is likely because pharmacies are a fundamental service that address healthcare.

Fig. 16. Index of pharmacy coverage per population volume and age bracket. Source: Sonata LI (TAPTAP) | INE
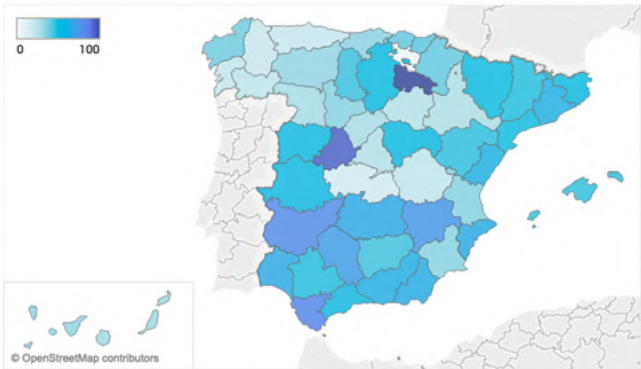

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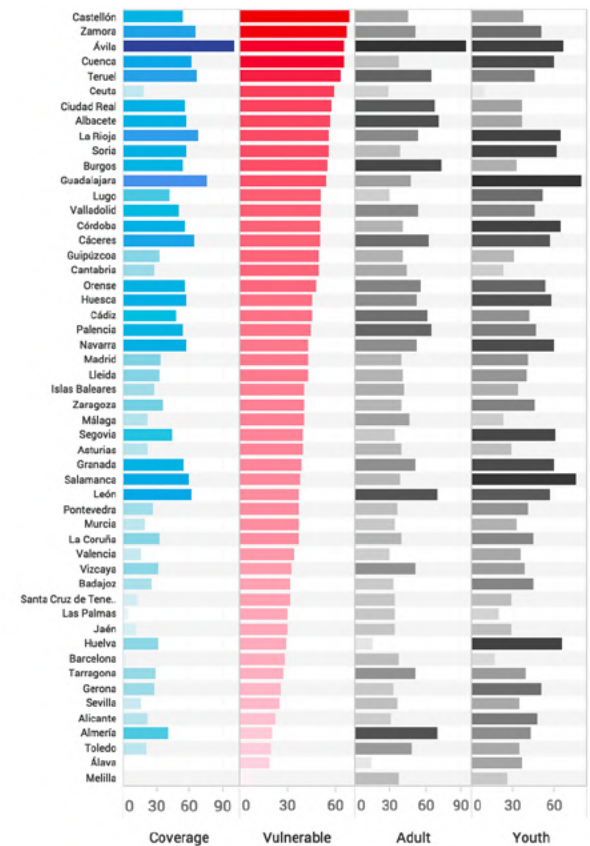
Supermarket and food services coverage per population density

Fig. 18. Index of supermarket coverage per population density.
Source: Sonata LI (TAPTAP) | INE

La Rioja, Avila and Cádiz have the highest supermarket coverage per population density. If we incorporate into the analysis the index of adult population (the group most likely to visit the supermarket), Ávila, Alemería and Albacete have the most coverage. The lower the coverage of these POIs, the higher rate of mobility it can generate.
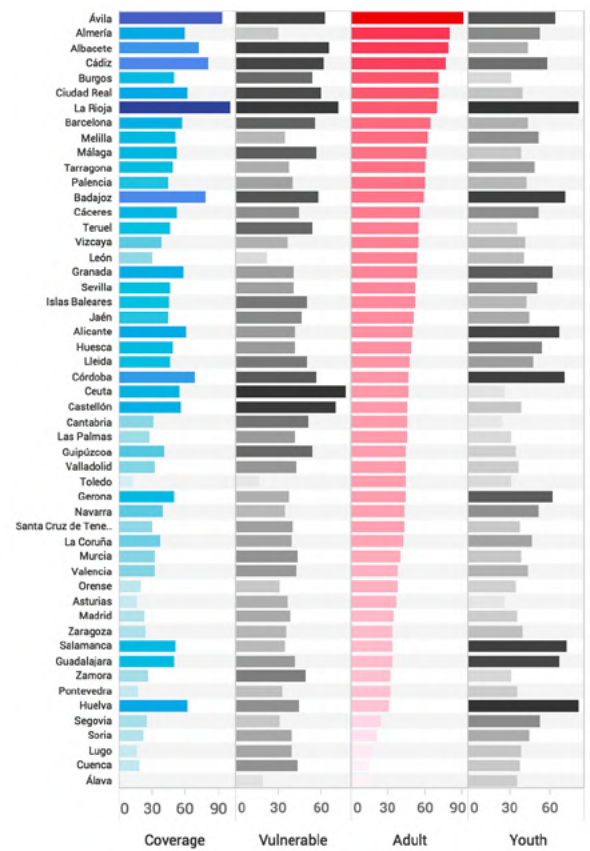
Fig. 20. Hyperlocal POI Analysis: Traffic in an Alcobendas (Madrid, Spain) supermarket. *Source: Sonata LI (TAPTAP) | UC3M | Predicio*

The hyperlocal point of interest analysis for a supermarket in Alcobendas provides different insights. It shows that even though markets are among the POIs most visited, the total traffic has significantly dropped below the baseline by 90%.

Fig. 19. Index of supermarket coverage per population volume and age bracket. *Source: Sonata LI (TAPTAP) | INE*

Coverage of transportation stations per population density

Fig. 21. Index of transportation stations coverage per population density.
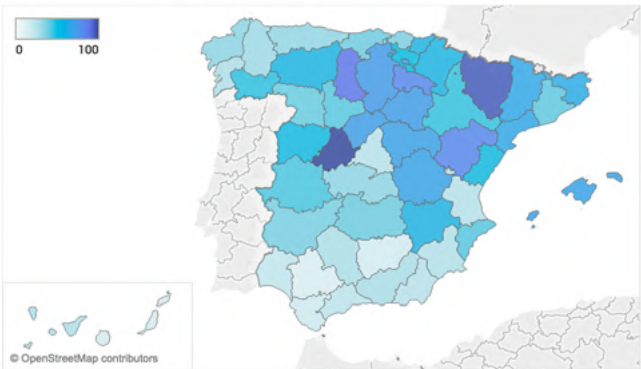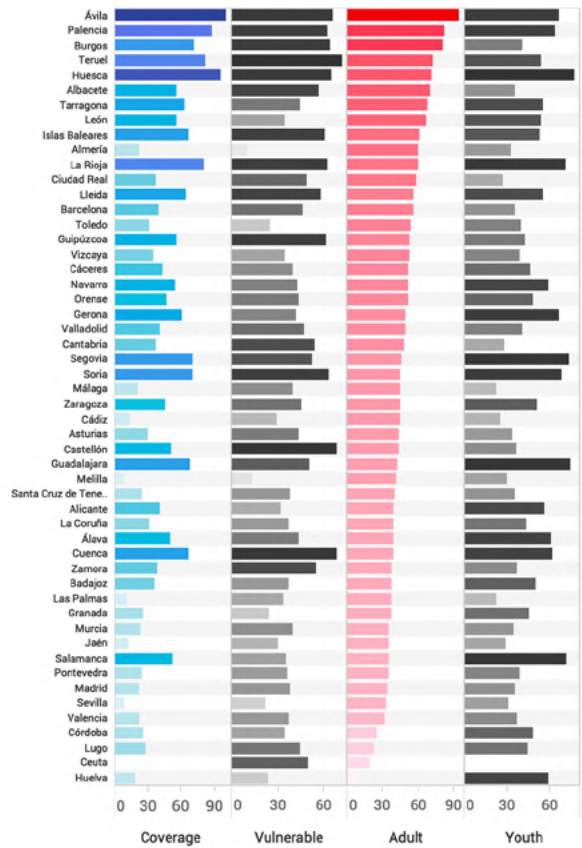*Source: Sonata LI (TAPTAP) | INE*

Fig. 22 shows that Castile and León have the highest coverage rate of transport services per adult population, the segment most likely to use these services. Madrid and Barcelona have less coverage compared to population density and therefore may have higher demand for these services which raises the risk of contagion.

Fig. 23. Hyperlocal POI Analysis: Traffic in Atocha Station (Madrid, Spain). Source: Sonata LI (TAPTAP) | UC3M | Predicio
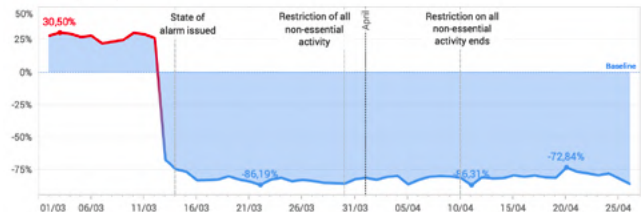
This graph shows hyperlocal foot traffic for one of the busiest train stations in Madrid. Traffic has dropped to nearly 90% below the baseline.

Fig. 22. Index of transportation stations coverage per population volume and age bracket. Source: Sonata LI (TAPTAP) | INE

Multivariable Analysis

COVID NATIONAL ANALYSIS

Fig. 24. Evolution of cases, deaths, hospitalizations, recovered and ICU patients. Cumulative Data. *Source: Ministerio de Sanidad*
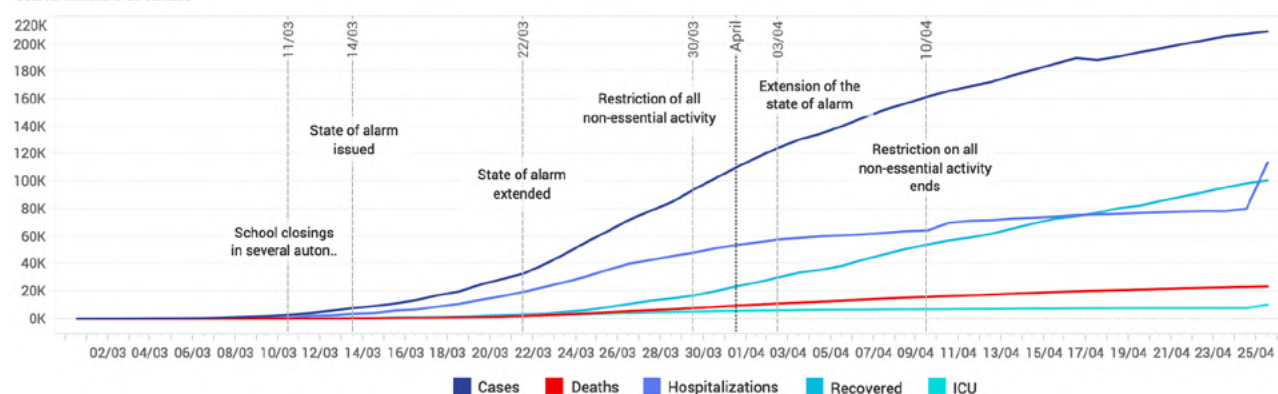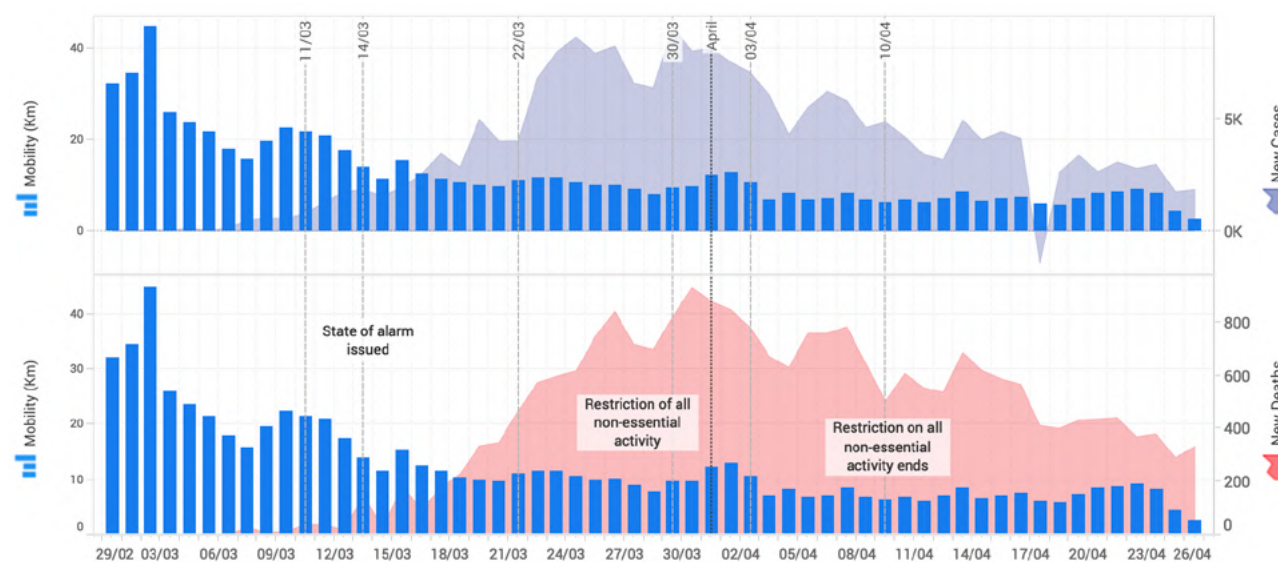

Fig. 25. Mobility and COVID-19 Indicators. *Source: Sonata LI (TAPTAP) | Ministerio de Sanidad | UC3M | Predicio | Tamoco*

Both deaths and new cases peak around April 1 – about 2 weeks after the activation of quarantine measures – and then begin to decline. As new cases always precede deaths, the rate of new cases slows faster than the death rate, but both follow the same downward trend.

Although the pace of new deaths is a consequence not only of mobility, the peak of deaths appears approximately 15 days after mobility falls in a stable pattern.

Cumulative cases and deaths per autonomous community

Fig. 26. Rate of cumulative incidents. *Source: Ministerio de Sanidad*
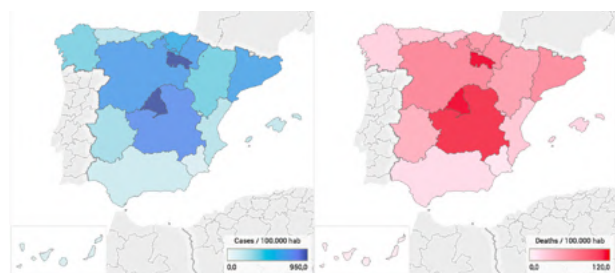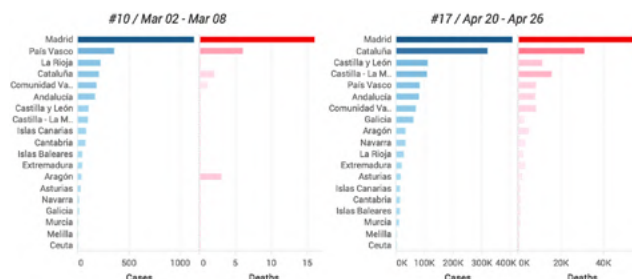

**Fig. 27. Casos acumulados y muertes por CCAA.** *Source: Ministerio de Sanidad*

When examined against geographics, you can monitor the evolution of the pandemic according to contextual, population or mobility variables to understand more about how the pandemic develops and establish relationships between variables.

COVID REGIONAL ANALYSIS

The next sequence shows data from the 3 blocks of analysis: Demographics (vulnerability measured by age), Geo Context (hospital coverage) and Behavior (user mobility). Using Leganés, a Spanish city with high incident rates, as a reference, a very strong correlation between the 3 blocks and the rate of exposure emerges.

Fig. 28. Correlation between indicators, Leganes (Madrid) *Source: Sonata LI (TAPTAP) | INE*
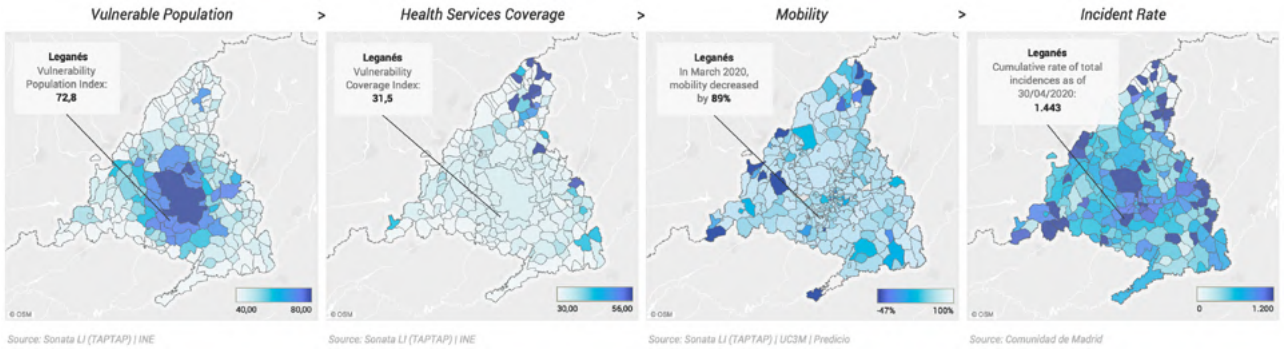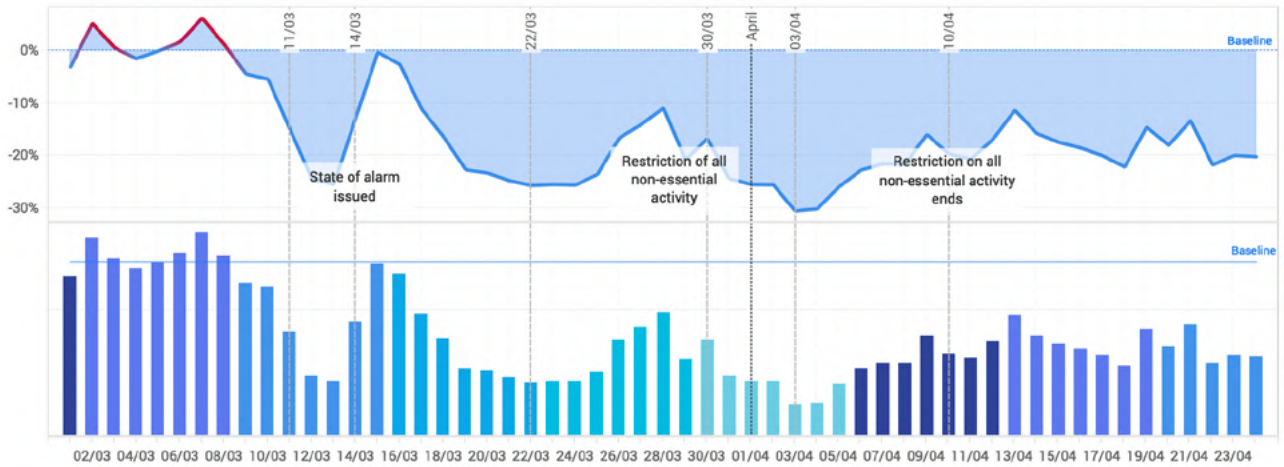

With these datasets we are able to build a multivariable index that explains and foresees possible degrees of infection per geographic area.

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Audiences. Behavioral Changes

DIGITAL BEHAVIOR

Fig. 29. variation of digital traffic with a 3G/4G connection. *Source: Sonata LI (TAPTAP)*

The baseline here represents the average number of devices using cellular networks to provide internet connectivity prior to COVID. Post-confinement, connections to a mobile network dropped by about 30%, while wifi connections increased. As wifi is most common at home or at work, and data is used on the go, we assume that this change is due to a decrease in mobility.

After April 12, network connections grew, which could indicate more mobility after the initial confinement.

Fig. 30. Shopping Center Purchases in City Peripheries, Pre-Confinement.
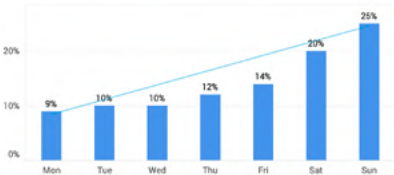*Source: Sonata LI (TAPTAP)*

Fig. 31. Shopping Center Purchases in City Centers, Pre-Confinement.
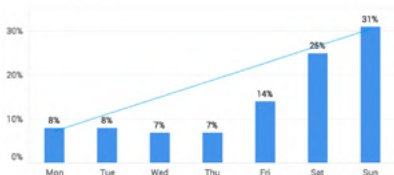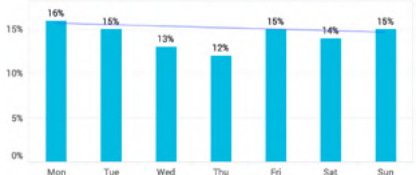*Source: Sonata LI (TAPTAP)*

Fig. 32. Purchases in Confinement.
Source: Sonata LI (TAPTAP)

Concentrated Behavior Pre-Confinement

Prior to confinement, behavior at the physical point of sale is concentrated on the weekend and more pronounced in shopping centers than urban areas.

Nearly half the physical purchases made are done in just two days of the week.

Seasonality patterns no longer apply to purchase behavior

Individual and shopping behavior does not follow traditional patterns. The days with low activity become days with more visits, while weekends are the same or even below the daily average.

The linear nature of shopping habits show it is no longer a leisure activity.

APPENDIX:

<u>Working With Location Data: A Technical Perspective</u>

The aforementioned location data is collected anonymously via mobile applications that have location services enabled. In each device, operating systems (like iOS & Android) merge multiple data types like GPS, WiFi or Bluetooth to provide accurate latitude and longitude coordinates, the most precise being a single GPS pinpoint (used for this study). To facilitate rapid technological analysis of location data, these pinpoints are converted into a geohash, which is a universal coding system used to identify locations at varying levels of precision and size. The latitude and longitude point(s) are hashed into a tile or block that can contain few or many points, according to the point of interest or in this case, the scope of the study. In addition to facilitating analysis, geo hashing has the dual benefit of protecting user privacy by essentially zooming out from their pinpoint location, injecting what is called, noise. The collaborators conducting this study selected a geohash that preserves individual privacy but ensures the accuracy of the study within tens and hundreds of meters depending on the analysis in question. A technique known as Gyration Radius was used to measure the distance each device has moved from its path center which is its most common location (like a residence). This technique allows us to calculate the number of KM moved throughout the day.

<u>A Representative Sample</u>

To ensure the accuracy and value of the study, a sample of location data (and device data) representative of the Spanish population was used. To arrive at this sample, TAPTAP and its collaborators curated and filtered data from millions of devices with billions of location data signals. To be able to provide a valuable and precise mobility analysis, only devices that generated multiple data signals from different sources at varying windows of time throughout the entire day (thereby exhibiting a genuine change of location versus a micro movement like a change of room) were applied to the study. The data is variable and temporal by nature as it changes according to the features of the mobile application, device operating system and user consumption patterns. To bypass the temporal nature of the data, we work with data partners like Tamoco or Predicio who refresh location data every few minutes (around 100 - 200 daily signals per unique device) tantamount to at least 5 location data samples per device per day. The resulting output of the accumulation of these moving parts, which include anonymous user ID hash, time, location as well as additional, non-personal metadata and location accuracy, is a location object (location event). The location object is the individual unit, composed of all of these parts, that enables us to analyze the data collectively for each location.

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