Time correlation between the mobility restrictions implemented in UAE and their effect on the reduction of COVID-19 spread.

Introduction

Since the COVID-19 pandemic started, the UAE Government has implemented a number of mobility restrictions to reduce the spread of the disease. Restrictions started in March 2020 followed by a lockdown in April 20, with partial lifting of the restrictions in May to allow for a reinjection of Businesses coinciding with local holidays.

But against this backdrop of full/none/partial mobility restrictions when did their effects become visible? and which measures have been the most effective ones?

We will begin the data acquisition phase with a predefined time frame (Feb-June 20) and two key data sources: the Google Community Mobility reports and "Ourworldindata OWID" COVID-19 reports. This data will be supplemented where required to be able to answer our questions, and contextualised by plotting it against the different measures taken by the UAE government during & after lockdown (e.g. reopening of shops, restaurants, partial return to work, etc).

Initially we will analyse the daily trend of ascending/descending COVID cases alone and in relation to the mobility measures, and then we will apply different algorithms to create a prediction model specific to UAE. All observations will be cross-checked against a number of variables that can influence the outcome of the study (test result turnaround time, test capacity in the market etc). These variables will be acquired through domain knowledge, deep diving in the sequence of events that affected UAE during the period and the overall Government measures to contain the virus.

The conclusions from this model will help predict a time lag between the implementation of mobility measures and their impact on new cases. It will also present an ideal mix of mobility measures applicable to UAE based on an effectiveness range. These finding can help the UAE Government understand which mobility measures had the fastest effect and largest contribution in reducing the spread of COVID-19 so it serves as a decision-making tool for future pandemics.

Background

Since the outbreak of Covid-19 in Wuhan, China in December 2019[i] and the subsequent spread of the virus around the world, social distancing has been seen as one of the main public policy methods to reduce the spread of the virus globally[ii]. In order to expand & improve our understanding of this domain knowledge, we reviewed various types of research papers.

Specifically, a lot of research has been done which correlates a reduction in urban mobility to a reduction in Covid-19 cases. This has been supported from different parts of the world. For example, Badr et al[iii] (2020), in their study across 25 counties in the USA, conclude that there is a strong correlation between mobility patterns in these counties and the rates of Covid-19 cases. Similarly, Kraemer et al[iv] (2020) describe a comparable pattern in China. Elaborating on this pattern, Zhou et al (2020) claim "mobility reduction of 20–60% within the city had a notable effect on controlling COVID-19 spread"[v]. Studies from Europe resonate a similar trend with Iacus et al (2020) claiming "mobility alone can explain up to 92% of the initial spread"[vi] in France and Italy.

However, while global research as well as public policy widely support the link between urban mobility and the spread of Covid-19, there remains the need to look more deeply into the granular dynamics of this correlation. For instance, when do these changes in mobility start to take effect?

Badr et al (2020) claim “the effect of **changes in mobility patterns**, which dropped by 35–63% relative to the normal conditions, on COVID-19 transmission are **not likely to be perceptible for 9–12 days, and potentially up to 3 weeks**.”[vii] Similarly, Iacus et al (2020) say “the typical **lagged positive effect of reduced human mobility on reducing excess deaths is around 14–20 days**.”[viii] Likewise, Zhou et al (2020) claim “a flattening of the peak number of cases by 33% […] and delay to the peak number by 2 weeks with a 20% restriction, 66% […] reduction and **4 week delay with a 40% restriction**, and 91% […] reduction and 14 week delay with a 60% restriction.” [ix]

In the UAE, overall, academic research on Covid-19 and urban mobility is limited. Studies such as that by IQ data[x] examine how urban mobility changed in the UAE as a result of Covid-19 restrictions and people’s sentiments about these measures. AlQutob et al (2020) [xi] look at the best strategy to exist from restrictions for countries such as the UAE. Jabeen et al (2020)[xii] compare the UAE response to Covid-19 in terms of mobility and travel restrictions with countries such as Pakistan and Vietnam. Bentout et al (2020)[xiii] study the dynamic of age groups within the spread of Covid-19 in the UAE. In our requirement analysis we identified that, while there is some literature that broadly looks at some aspects of urban mobility restrictions in the UAE during Covid-19, there is a lack of detailed insights into this correlation.

The current research project aims to better quantify this correlation in the context of the UAE, thus helping with the management of current and future pandemics. It also seeks to understand the effectiveness of urban mobility measures across different industries/ businesses in the UAE.

Method

Research questions / Hypotheses

Our essential research question is: What is the time gap between the changes in urban mobility and its effects on the number of new COVID-19 cases in the UAE? In other words: When does the effect of changes in mobility ‘kick in’? And does the time lag & effectiveness vary across different industries/businesses? In light of this below are our hypotheses:

Hypothesis 1: In the UAE, we estimate a time lag ranging between 9-15 days, between mobility restrictions of up to 40% and their impact on Covid-19 cases.

Hypothesis 2: We anticipate this time lag to vary across different categories in the UAE (retail, transport, workplace). This time lag is linked to the effectiveness of the restrictions taken to contain the spread of Covid-19.

Data & Data processing

This study relies on datasets from the Google Community Mobility Reports and OWID ‘’Ourworldindata’’ website. We have reviewed the files carefully to select the most relevant information to meet our objectives. We have also considered the data definitions from both sites & the metrics to merge/link the information correctly. We have come up with a first draft but this will be an iterative process.

For hypothesis 1 we will select the following variables from the <u>Mobility dataset</u>:

- Country
- Date
- residential_percent_change_from_baseline

For hypothesis 2, we will use the additional variables:

- retail_and_recreation_percent_change_from_baseline
- grocery_and_pharmacy_percent_change_from_baseline
- transit_stations_percent_change_from_baseline
- workplaces_percent_change_from_baseline.

(Note: The variables selected are not exclusive and might be supplemented upon further investigation.)

In the data processing stage, the dates variable will be filtered from the 29th of Feb, when the *residential change from baseline* value was zero until the 21st of June, which is 4 weeks after the mobility data reached the maximal value of change. We will possibly consider a wider data range in 2020 (to be determined) to look at the medium-term effect of the mobility measures.

Some caveats:

- We must plot the data to verify the time lag period before producing the regression models.
- The time lag caused by the processing time of Covid-19 swab test will be used as one of the variables, but we have not found to date an official dataset that shows the processing time over the period chosen for the study, so we will rely on credible publications or government press releases.
- The data presents blank rows over several days in the Um Al Quwain emirate. It is unclear at this point the reason why and whether that data is consolidated at higher level. We must determine the relevance of this data, how it is consolidated, and the weight given to each emirate in order to remove the bias.

Metrics

Some of the variables that we will utilise in designing the algorithm include:
From the OWID file:

- *New_cases:* number of new positive Covid-19 cases confirmed on the specified date.
- *New_tests:* number of Covid-19 tests conducted on the specified date.
- *New_tests_per_cases:* number of tests done to find a COVID-19 case in a country. It is another way of looking at how widespread the testing is relative to the scale of outbreak.

Total (cumulative) trends will be plotted against daily where applicable for better understanding of the model.

From the Google Mobility file: The following variables indicate % change in mobility in designated areas from pre-Covid time to specified date.

- *Residential_percentage_change_from_baseline*
- *Retail_and_recreation_percentage_change_from_baseline*
- *Grocery_and_pharmacy_percentage_change_from_baseline*
- *Transit_stations_percentage_change_from_baseline*
- *Workplace_percentage_change_from_baseline*

Some of the metrics that will help confirm measure the validity/effectiveness of the model will include:

- Taking a baseline of 0% mobility restrictions (Jan-early Feb 20) and a scenario of 100% mobility restrictions (Lockdown in April) there will be a strong correlation (expressed by the R coefficient) between overall mobility restrictions of 40% and a decrease of new COVID cases visible between a time range of 9-15 days.
    - This correlation will be supported with a cumulative slowdown of the virus growth rate (*Total_cases_per_million*) represented by daily/weekly trend analysis. Figures

will be calibrated to allow for an increased number of test capability in the market *(New_Tests*).

- If the first metric is True, and assuming the same baseline, there will be a correlation between the individual mobility variables and a reduction of new Covid cases within the same time range of 9-15 days. The model will isolate the variables with the stronger correlation and faster impact (expressed by the day range).
- R^2 value>0.6 for the regression model.
- P value <0.05 for the overall hypothesis and for the most effective individual variables.

Modelling

Once we have acquired all the elements necessary to support our hypothesis through domain knowledge and data understanding, we will proceed to modelling the Algorithm. We will use supervised machine learning model (Regression analysis) to establish the best causality model between the different mobility measures and their effect on COVID cases, as well as the time lag between the measures being implemented and the appearance of new cases. Key challenge will be defining the correct number of variables affecting the regression models, which might lie outside the primary scope of the study. In order to establish regression, we will use other algorithms like clustering to help us establish relationships in data. We will refine the model through several iterations to achieve the best regression algorithms.
We expect that the final outcome of the data lifecycle will prove our hypothesis, obtaining a response & effectiveness range applicable to UAE.

The Null hypothesis would equal:

- An inconclusive/negative correlation between mobility measures and spread of the virus.
- An inconclusive time lag between the mobility measures and new cases detected.
- The inability to attribute an effectiveness range to the different mobility categories.

There are a number of limitations that can affect the result of our study:

- There have been other measures implemented to reduce the spread of COVID-19 like the use of masks. There is a risk to overstate the effectiveness of the mobility measures when considered in isolation.
- The Place Categories in the Google Community Mobility report needs to be contextualised for UAE purposes, potentially altering the baselines and mobility percentages. E.g. Transit stations data might be affected by the Summer season, and Retail & recreation should be supplemented with hotel booking information.
- Religious holidays, the Summer season and other environmental factors.
- The Department of Health- Abu Dhabi (HAAD) and Dubai Health Authority (DHA) have issued different testing procedures over the last few months. This information can affect the number of tests taken and thus the detection rate.

Based on the results and the development of the model we will develop a deployment strategy with the appropriate stakeholders in due course.

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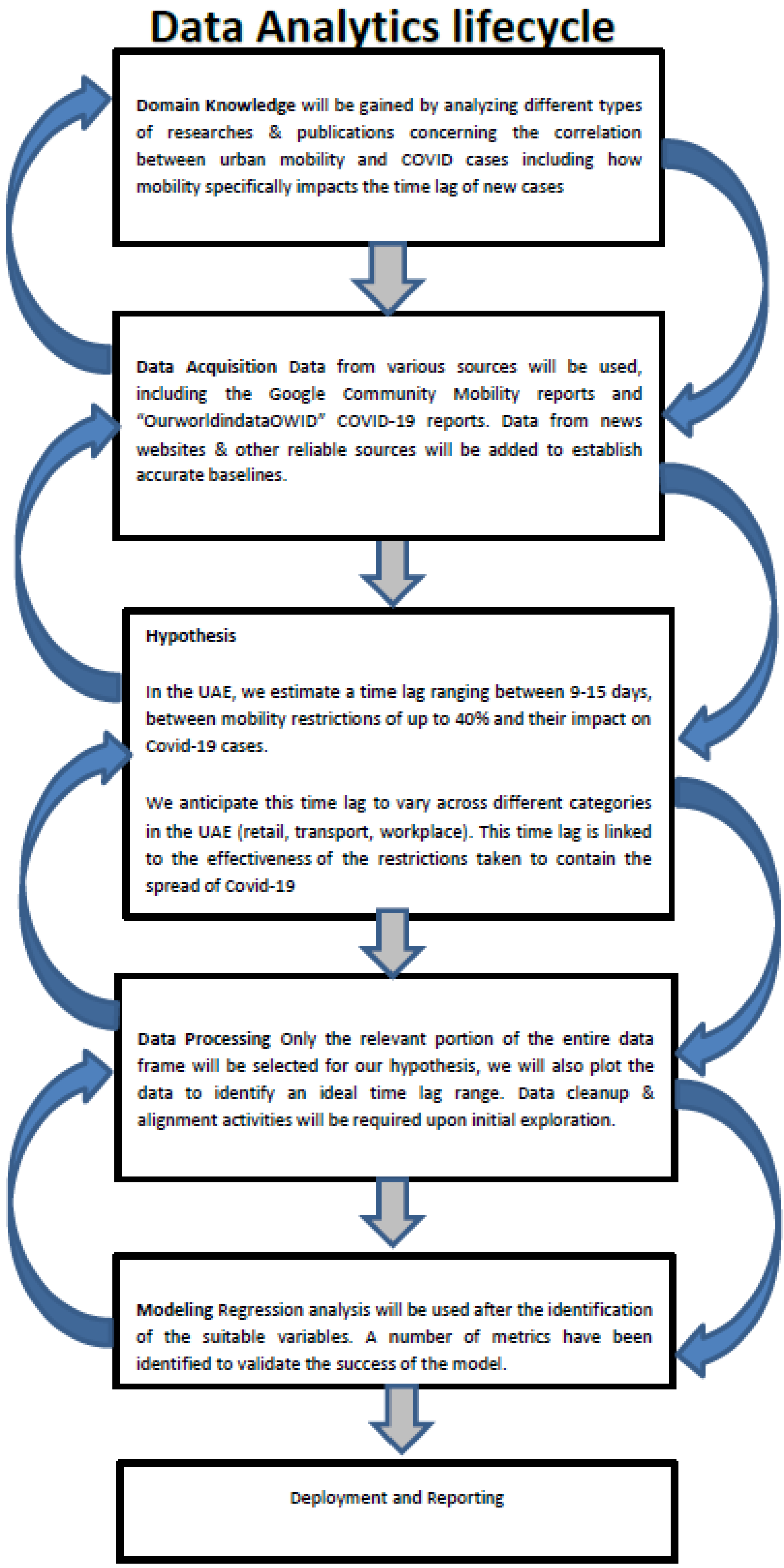
Appendix


Data Analytics lifecycle
Domain Knowledge will be gained by analyzing different types of researches & publications concerning the correlation between urban mobility and COVID cases including how mobility specifically impacts the time lag of new cases
Data Acquisition Data from various sources will be used, including the Google Community Mobility reports and "OurworldindataOWID" COVID-19 reports. Data from news websites & other reliable sources will be added to establish accurate baselines.
Hypothesis
In the UAE, we estimate a time lag ranging between 9-15 days, between mobility restrictions of up to 40% and their impact on Covid-19 cases.
We anticipate this time lag to vary across different categories in the UAE (retail, transport, workplace). This time lag is linked to the effectiveness of the restrictions taken to contain the spread of Covid-19
Data Processing Only the relevant portion of the entire data frame will be selected for our hypothesis, we will also plot the data to identify an ideal time lag range. Data cleanup & alignment activities will be required upon initial exploration.
Modeling Regression analysis will be used after the identification of the suitable variables. A number of metrics have been identified to validate the success of the model.
Deployment and Reporting