# 27/05/2020

Aggregating on country and phase (short)

1. Code Phase=0 if country is in restriction (1 if in relaxation).
   1. Restriction: when index is going up or staying constant
   2. Relaxation: from when it’s reduced onwards until it goes up again. Only Turkey I think was one such instance but I think it’s an anomaly
   3. Challenge: Every country might have as many restriction and relaxation periods as Oxford categories
      1. Solution 1: if we are to make our entire analysis only on one aspect of policy (combined with one dimension of Google Movement), then no worries.
      2. Solution 2: maybe we define lockdown when certain conditions are met and we register the date when the last of these conditions was met and relaxation when any of the 3 conditions was lifted.
2. Elastic net regressions to identify the right behavioural variable to be used. Risktaking very promising.
   1. Note that we might need to run elastic nets for 15 dependent variables (8-9 Oxford policies and 6-7 Google sub-categories).
   2. Include household residents
   3. Include good weather variable
3. The duration of each phase might be telling as well.
   1. Might correlate itself with behavioural measures (e.g. patience).

Aggregating on Country (long)

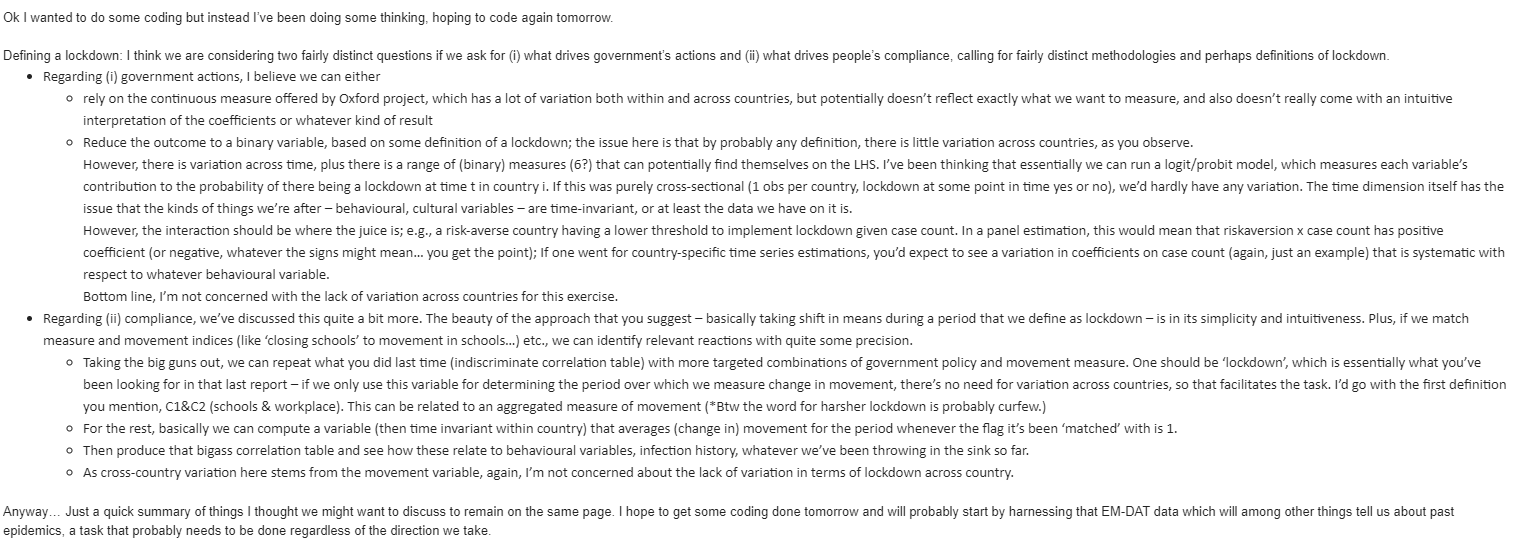
1. After we identify behavioural measures, sub-policies and sub-movements we can consider fancier measures (like ARDA) to calculate adherence.
2. The duration

# 28/05/2020

* The more I think about it, the more I come to realise that finding a universal criterion upon which we can binarize lockdown is really hard if not impossible.
* Perhaps a way to go about it is to go on a very micro level. Here is a strategy for looking at more disaggregated data and try to reverse engineer the external shocks we should be looking for (if this is possible). Here are the steps:
  + Let’s pick a country and quantify the daily differences in movement by taking first differences.
  + Then, let’s normalise these differences and test the days when the drop in movement was more than 2 standard deviations from the mean drop over a certain period.
  + Is there something special about these days? Was there a policy implementation? If so, what sort of policy was it?
    - Disaggregate further: do the same exercise for this country for a every Google variable.
      * Disaggregate even further: do the same exercise for every city of this country. For the UK we have daily data for 153 cities!

# 12/06/2020

## Country level

* Redo the “Kitchen and Sink” correlation table (KSC-table) but this time, correctly.
  + In fact, we should probably do three of those tables.
    - One where we focus on a country’s decision for **policies**. Factors:
      * Foreign influence
        + Recent paper: <https://www.aeaweb.org/articles?id=10.1257/jel.20201481&from=f>
      * State of the economy (cyclicality included). For example, Greece went hard during the early phase and plans to reopen everything during the peak-touristic period.
      * Health care capacity
      * Household occupants
    - One where we focus on people’s **compliance**. Factors:
      * Behavioural measures
      * Weather
    - **Efficiency**
      * This is more composite. Takes into account policy and compliance.
      * High efficiency is measured in total cases/deaths as a function of intensity of measures and movement reduction.
  + Challenges:
    - How continuous/ discrete do we want our policy index to be?
      * This point is discussed in the email Lio sent on June 1st:
        + 
      * Let’s try many possible indexes, throw them in the KSC table and take it from there

## Within country level

Early thoughts here:

* “I was thinking that it might be interesting to look within certain countries for which we have a lot of reliable info. For example, Google records the movement in 160 cities in the UK. The cool thing about this exercise is that within country analysis (like the UK in this example) offers us a singular and unambiguous time stamp for the introduction of a policy. Yet, I am fairly sure we will observe significant variation across different cities. What predicts this variation? This exercise can help us sharpen the tools for the country level  analysis or make for an interesting study on its own, provided the results are juicy enough. Sure, we don't have access to behavioural measures at a city level. But we do have access (or can potentially find) for avg income, population density, household residents (?), temperature/weather...etc.
* A challenge: we start dealing with big data, even when we look at a single country: 160 cities\*120 days \*10 (long format data that R handles best)
* An interesting advantage: look at specific events like the George Floyd death and how they impacted the trend.

## Main analysis

How will the main analysis look? We have variables that change by the day like Movement (and derivatives), Policy Index (and derivatives), Weather and the rest that are country specific.

|  |  |  |
| --- | --- | --- |
|  | Daily | SubCountry |
| Movement | 1 | 1 |
| Policy Oxford | 1 | 0 |
| Policy Corona | 1 | 1 |
| Behavuoural | 0 | 0 |
| Economy | 0 | ? |
| Covid | 1 | ? |

“?” means that for some we have info in sub-regions of a country too.

The amount of information will influence the type of analysis. If the primary regression is regarding movement (and derivatives) we could run a time series with country-fixed effects captured by the variables that don’t change…

If we want to run a more cross-section analysis, then we might want to find an aggregation rule for the variables that change daily.