What are the true effects of lockdowns and consequences of relaxations?

1 Introduction

Lockdown, as one of the social isolation restrictions during COVID-19, has been increasingly implemented by many countries all over the world. From 5th November 2020, the UK went into a second national lockdown and this did decrease the new cases effectively.

However, after the end of the second national lockdown in the UK, there is a serious explosion of the epidemic among the country, especially in London. It seems like post-lockdown period is even more serious than before-lockdown period. It is natural to ask the true effects of lockdown and the consequences of relaxing the lockdowns.

Also, although London suffers from a severe epidemic during post-lockdown, there are regional differences among the boroughs. It is worthy to study why some boroughs behave well while others behave worse.

To answer the above-mentioned questions, this report focuses on two parts:

1) Compare the lockdown effects on different regions in the UK by using SIR model.

2) Find out how the socio-economic and mobility factors affect the development of COVID-19 in each London boroughs.

2 Literature review

2.1 Mathematical modelling

Mathematical modelling of epidemics is an effective method to investigate the development and spread of the virus and in turn help governments optimize anti-epidemic measures.

Many studies focus on developing models to model the effects of lockdowns. Susceptible-infected-recovered (SIR) models and its variations are developed in many studies. Alvarez *et al.*(2020) use SIR model and a linear economy to help solve planner's dynamic control problem. Acemoglu *et al.*(2020) study targeted lockdowns in a multi-group SIR model and find long and strict lockdowns are beneficial to the most vulnerable group.

Bagal *et al.* use classic SIR model to study several lockdowns in India and suggest further strict interventions should be performed. Glass (2020) develops two-stage SEIR model to fit the data and a three-stage SEIR models to investigate various levels of relaxations. The results indicate that the relaxations ranging from 31% to 57% can lead to significant second waves for European countries.

2.2 Determinants of COVID-19

The determinants of COVID-19 include socio-economic factors as well as mobilipty patterns.

Stojkoski *et al.* (2020) find some determinants with strong evidence including overweight, population density, tourism and elder population. Platt and Warwick (2020) suggest that a third of the working-age population black Africans are employed in keyworker roles which means a higher risk of infection.

Askitas *et al.*(2020) suggest lockdown policies such as cancelling public events and restricting private gatherings can change the population mobility patterns and then control the pandemic.

3 Methods

3.1 Fitting SIR model to COVID-19 data

We will fit several SIR models to real data and estimate the key parameters.

The description of SIR model is as follows:

$$\frac{dS}{dt} = -\beta(t)\frac{SI}{N}$$

$$\frac{dI}{dt} = \beta(t)\frac{SI}{N} - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

N is the total population of each region, S, I, R are the susceptible, infected and removed (or recovered) groups. γ represents the removal or recovery rate and β represents the effective transmission rate.

The aim of the lockdown is to reduce β. So, we focus on the estimation of β in different stages of COVID-19, and we need to specify the value of γ which is equal to $1/t_i$ where t_i represents the mean infectious period. We take other researches as reference and set t_i to 3.4 days which is the estimates of infectious period in China (Glass, 2020; Li *et al.*, 2020).

Then we will estimate β in three stages for nine regions in the UK. Stage1 is from 1 August 2020 to 4 November which is the before-lockdown period. Stage2 is from 5 November to 2 December, the lockdown period, and Stage3 is till 4 January 2021, after which the third national lockdown begins.

Finally, we will calculate the basic reproduction number R, which represents the number of individuals infected by a single individual:

$$R = \frac{\beta}{\gamma}$$

The COVID-19 data used in this report comes from 'Coronavirus (COVID-19) in the UK'[1].

3.2 Panel Data Model

In this part, we will use three types of data:

1) COVID-19 related data

2) Socio-economic data

We collect the population, the percentage of working-age population with no qualifications, the percentage of 65+ old people, the percentage of black people and the average weekly pay of each London borough.

3) Mobility data

The data is collected from 'COVID-19 Community Mobility Report'[2] published by Google. This dataset shows how population visits to different kinds of places are changing. We choose Grocery & pharmacy, Transit stations, Retail & recreation, Residential and Workplaces as mobility data.

The dependent variable is the COVID-19 rate of the region:

$$Covidrate_{it} = \frac{Cumcases_{it}}{population_i}$$

The independent variables include the change percentage to 5 types of places which are time-variant, and the rate of old people, black people, have-no-qualifications people, and the normalized pay, which are all time-invariant variables. To make Pay is comparable with other rates, we adjust it by:

$$pay_i = \frac{pay_i - minpay_i}{maxpay_i - \ minpay_i} * 100$$

We need to use Hausman Test to judge if it is proper to choose random effects model firstly:

$$H0: individual\ random\ effects\ are\ exogenous$$

If the null hypothesis is rejected, it is not suitable to use random effects model, however, we still want to study the time-invariable variables, we will then use instrumental variables in the random effects model.

We will construct three models from three stages to see the effects of each variable.

[1] Coronavirus (COVID-19) in the UK

[2] COVID-19 Community Mobility Report

4 Results

4.1 Fitting results of SIR models

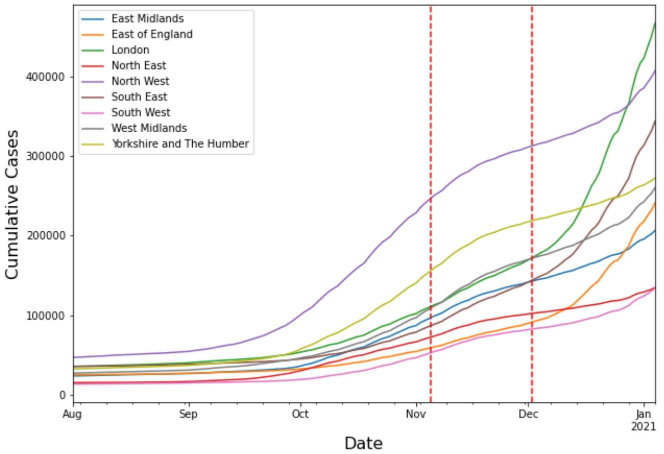

Figure 1 Timeline of Cumulative COVID-19 cases in nine regions

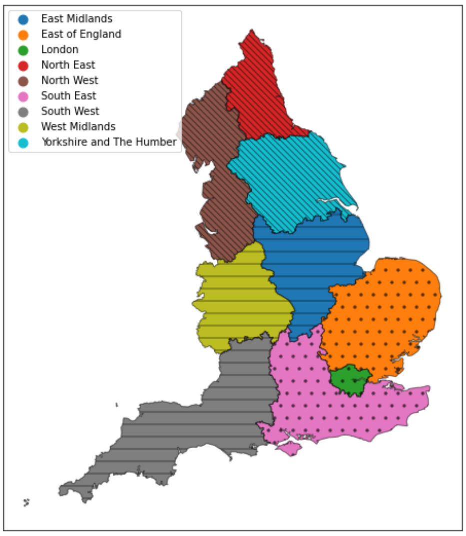

Figure 2 Initial division of regions

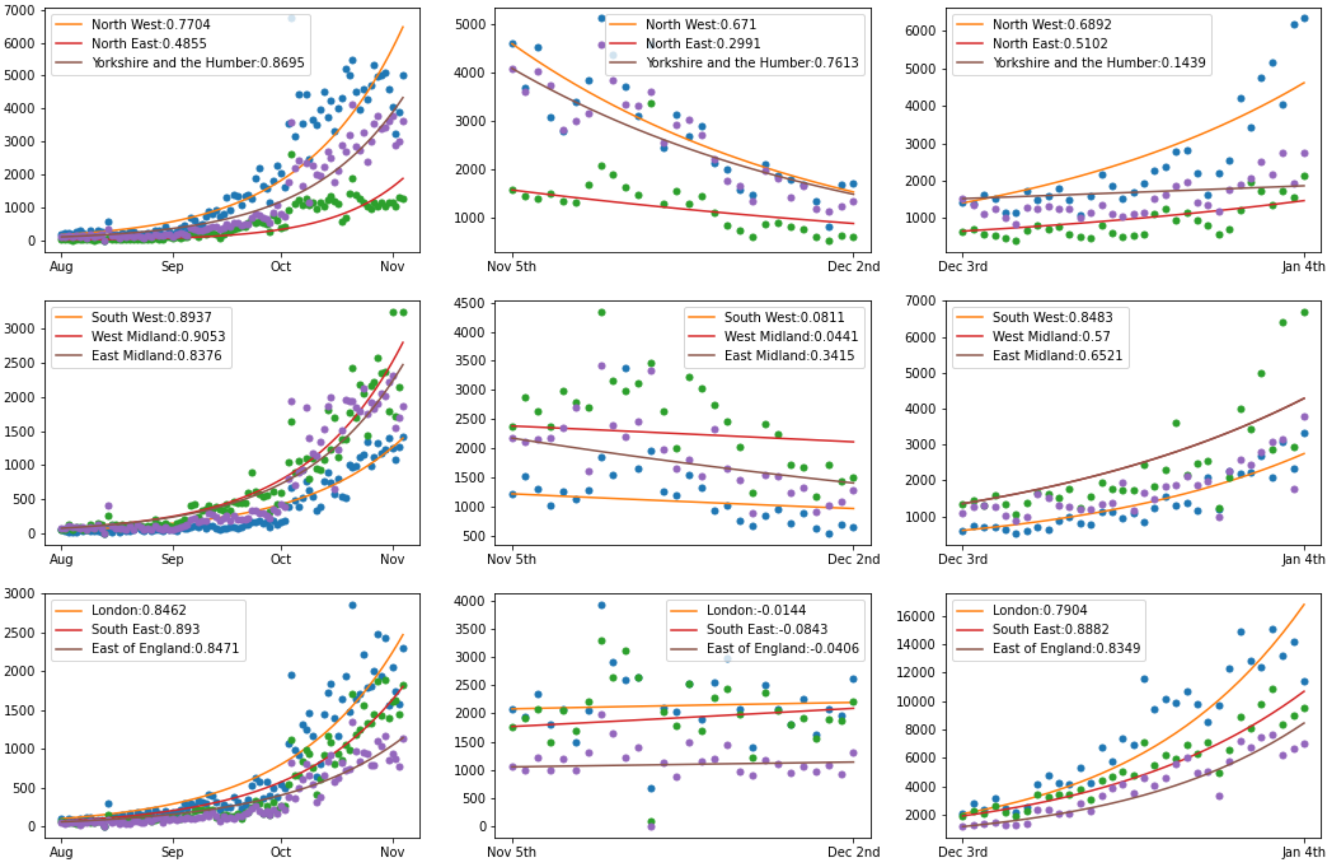

Figure 3 Fitting results of SIR models

Figure1 shows the development of cumulative COVID-19 cases in nine regions in the UK. Based on their trends and location, we initially divide them into three groups (Figure2) to better visualize them in Figure3.

Figure3 shows the fitting lines and R square of all the regions in three stages. The vertical axis represents the new cases.

In Stage1, we can see SIR model has good fitting results. North West, and Yorkshire and the Humber have the top two new cases. In Stage2, however, all the fitting results are not good expect for the two regions we just mentioned. This implys that lockdown has faster and more effective effects on worst-hit areas. During the lockdown, the new cases of London, South East, and East of England are still increasing slightly. These regions also suffer from a rather severe virus explosion in Stage3.

Table 1 Basic reproduction number R in each region and stage

Region	population	R_{Stage1}	R_{Stage2}	R_{Stage3}
London	8961989	1.114542	1.0078	1.22604
South East	9180135	1.115846	1.0220	1.18456
East of England	6236072	1.105521	1.0108	1.21176
North East	2669941	1.176435	0.9289	1.088
North West	7341196	1.132036	0.8633	1.12812
Yorkshire and the Humber	5502967	1.13458	0.8745	1.0234
East Midlands	4835928	1.1254	0.9466	1.10092
South West	5624696	0.97172	0.9717	1.1611
West Midlands	5934037	1.1373	0.9867	1.12472

Table1 shows the results of R. Compare R_{Stage2} with R_{Stage1}, we can see R significantly decreases in North East, North West and Yorkshire and the Humber. London, South East, East of England and South West have a higher R after the relaxation of lockdown than in the before-lockdown period. London has the highest R_{Stage3} among all the regions and suffers the most from the relaxation.

4.2 Panel Data Models

Figure4 shows the distribution of new cases and cumulative cases of COVID-19 on 4 January 2021. It is obvious that there are regional differences. In Stage3, the east of London is the worst-hit area, especially for Redbridge and Havering.

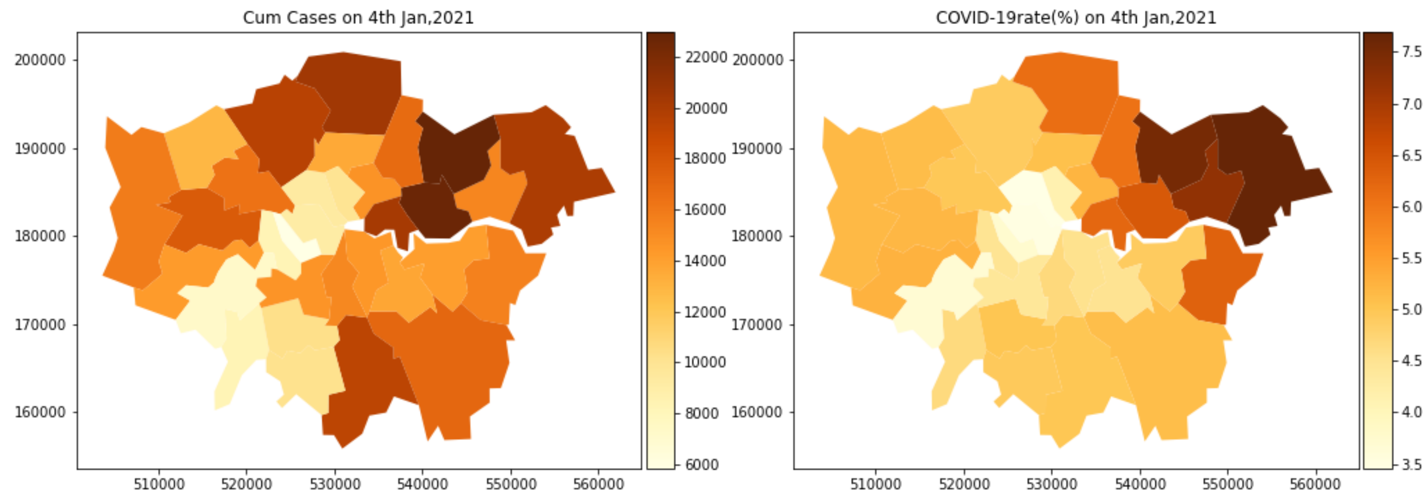

Figure 4 Cumulative cases and COVID-19 rate in London boroughs on 4 January 2021

All the Hausman Test results of the three models reject the null hyphothesis, so we finally choose random effects model with instrumental vairables. The formula is:

$$Covidrate_{it} = \beta_{1i} + \beta_2 retail\_recreation_{it} + \beta_3 transit\_stations_{it} + \beta_4 grocery\_pharmacy_{it} + \beta_5 residential_{it} + \beta_6 workplaces_{it} + e_{it}$$

where $\beta_{1i} = \overline{\beta_1} + u_i$

Table 2 Summary statistics of variables

	COVID rate	retail_and recreation	grocery_ and_pha rmacy	transit_ stations	work- places	residen -tial	pay (£)	old	Black rate	noqua
Min.	0.313	-96	-93	-97	-91	1	0	6.171	0	2.5
1st Qu	0.7018	-55	-17	-58	-54	11	8.712	9.226	6.685	4.7
Median	1.2766	-40	-11	-47	-44.5	15	11.278	12.055	9.407	6.35
Mean	1.645	-40.99	-13.31	-49.62	-42.98	15.52	14.452	11.818	11.245	6.622
3rd Qu	2.0859	-25	-6	-40	-34	19	18.156	13.648	16.58	8.225
Max.	7.6902	13	37	-14	4	40	37.753	17.494	23.31	10.8

Table 3 Model summary

Variables	Model1 (Stage1)	Model2 (Stage2)	Model3 (Stage3)
(Intercept)	0.5389 .	2.6234***	-0.5046
	(0.3226)	(0.4206)	(1.3658)
retail_recreation	0.0176***	0.0139***	-0.0267***
	(0.0009)	(0.0012)	(0.0027)
transit_stations	-0.0166***	0.0056*	-0.0509***
	(0.0012)	(0.0027)	(0.0044)
workplaces	0.0263***	0.0023	0.0254***
	(0.0008)	(0.0021)	(0.0041)
grocery_pharmacy	0.0046***	0.004*	0.0188***
	(0.0012)	(0.0017)	(0.0012)
residential	0.0724***	-0.01*	0.047***
	(0.0029)	(0.0045)	(0.0106)
black	0.0026	-0.0095	-0.009
	(0.0067)	(0.0084)	(0.0284)
pay	0.0075*	0.0159**	-0.0632***
	(0.0038)	(0.0049)	(0.0161)
noqua	0.0259 .	0.0499**	0.0942
	(0.0156)	(0.0194)	(0.0663)
old	-0.0104	-0.0079	0.0421
	(0.0147)	(0.0184)	(0.0624)
R-squared	0.4684	0.2694	0.7133
Adj. R-squared	0.4657	0.262	0.7108

Standard errors in parentheses. * p< .05, ** p< .01, *** p< .001

Table3 shows the summary of three models. We can see old and $black$are not significant in all models. pay and $noqua$ are sigfnificant and positive in the first two stages, which implys that the higher average income and the more people with no education qualifications, the higher COVID-19 rate. However, pay is negative and significant in Stage3.

As for the mobility factors, since mobility factors represent change rate from the baseline data, they are not absolute values, which means it is not easy to interpret the coefficients. Nevertheless, there are still some inspiring findings.

Except for residential places, the change percentage of visits to all other places are negative. Thus if the coefficients are postive, the bigger negative change of visits to these places, the lower COVID-19 rate. As for residential places, positive coefficient means that the bigger positive change of visits, the higher COVID-19 rate.

Comparing the coefficients of three stages, we find that in Stage2, during the lockdown period, the more visits to residential places, the lower COVID-19 rate while increase of visits to all other types of places will increase the rate. This is just the role of lockdown. If people can stay at home more, the epidemic can be in control. However, in Stage3, many coefficients reverse like $retail\_recreation$. A possible explanation is that in Stage3, the reduction of visits is not as big as that in the lockdown period, so even if the visits decrease to some extent, the COVID-19 still keeps developing.

5 Conclusion

In this report, we first use SIR model to estimate β and R in three stages for all the regions in the UK. The results indicate that the lockdown has the most beneficial effects on the North West, and Yorkshire and the Humber. However, the lockdown has slight effects in London, South East, and East of England. Also these regions suffers a lot from the relaxation of lockdown in Stage3.

Then we furtherly study the determinants that effect the epidemic in the boroughs of London. In the post-lockdown period, there is a negative correlation between average pay and the virus rate while stay postive in the first two stages. Besides, education is a significant factor in explaining the COVID-19 rate. As for the mobility patterns, the effects of limiting outdoor-time are most significant during the lockdown peroid. In contrast, in Stage3, the decrease of outdoor-time seems to be not efficient enough to reduce COVID-19 cases, maybe because the reduction is not big enough during this relaxation period.

In conclusion, the findings indicate that the lockdown does play a critical role in those regions which already had serious epidemic, and the mobility limitation is proved to be useful. However, as for London, the lockdown seems to be too short to play the role, and the relaxations even worsen the disease.

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