# "Stay Nearby or Get Checked": A Covid-19 Lockdown Exit Strategy

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April 10, 2020

**Abstract**

This paper repurposes the classic insight from network theory that long-distance connections drive disease propagation into a strategy for controlling a second wave of Covid-19. We simulate a scenario in which a lockdown is first imposed on a population and then partly lifted while long-range transmission is kept at a minimum. Simulated spreading patterns resemble contemporary distributions of Covid-19 across nations, regions, and provinces, providing some model validation. Results suggest that the proposed strategy may significantly flatten a second wave. We also find that post-lockdown flare-ups remain local longer, aiding geographical containment. Public policy may target long ties by heavily focusing medical testing and mobility tracking efforts on traffic and transport. This policy can be communicated to the general public as a simple and reasonable principle: Stay nearby or get checked.

## 1 Introduction

Many countries facing the spread of Covid-19 are currently in some form of lockdown in which person-to-person contact is severely restricted. The constraints thus placed on social and economic interaction have high cost. How to open up society once new infections have dwindled?

Here we explore the leverage gained from differentiating between short-distance and long-distance ties in post-lockdown policy. The idea is that the blockage of transmission through long-distance ties increases the effective *diameter* of a network, which is inversely related to the speed of propagation [1, 2]. In practice, such geographic differentiation may be achieved through location tracking technologies and prioritization of non-local travel and transport in policy restrictions, enforcement and medical testing. The relative sparsity of long-range ties may make tight control feasible through a focus of resources on a small number of key individuals or interactions.

Results show that reductions in transmission through long-range ties slow down Covid-19 to a much greater extent than reductions in short-range ties. Selective scrutiny of long-distance ties has two added benefits: Post-lockdown flare-ups of Covid-19 are local, allowing geographically focused interventions that are of limited economic damage and logistically more feasible. And social toll is diminished, as the intimacy of human relations and need for face-to-face contact are known to decrease sharply with geographical distance [3, 4, 5, 6, 7, 8, 9].

# 2 Related work

Social network models of disease spreading have been around for decades. What sets our work apart is an analysis of the epidemiological leverage of government policies that differentiate long-distance from short-distance ties in social networks.

## 2.1 Social network models of infectious disease spread

Many epidemiological studies assume random mixing of individuals within demographic subgroups (e.g. by age) [10]. However, most contact occurs between people who live very close to one another [11, 12]. We draw on the well-known small-world model of Watts and Strogatz [13] to capture the fundamental difference in viral risk between close-range and long-range ties: Close-range ties connect infected individuals with others who are already infected or are about to regardless. Long-range ties expose faraway contacts who would otherwise not be at risk and who may in turn infect others who are otherwise safe.

The small-world approach to the study of epidemiological dynamics is not new. Network analysis was introduced into mainstream epidemiology at the turn of the century to explicitly incorporate the contact structure among individuals. It is well known that diffusion processes on networks depend on the corresponding connectivity patterns [14]. Research has shown that subtle features of network structure can have a major impact on the outcome of an epidemic [15, 16]. Small-world networks are almost identical to lattice networks in which viruses spread slowly and locally [13, 17]. The subtle difference is a small portion of ties to distant localities on the lattice, producing a dramatic reduction in a network's diameter, which is inversely related to viral spread. The rapid spread of viruses through small-world networks makes them hard to contain in time within confined regions of a population. Past work has examined the effects of a range of network models on epidemiological dynamics [18, 19, 20].

A small-world SEIR model was used in [21] to model an influenza outbreak in the city of Orhan. In a study closest to ours, Small and Tse investigate disease spread in a small-world network with separate infection probabilities for short-distance and long-distance ties [22]. Using a SEIR model of the SARS epidemic dynamics they find that exponential growth in infection occurs upon onset of several non-local infections. They conclude that key to capturing the empirically observed transmission dynamics is differentiating local from non-local transmission probabilities. We build on this observation to explore the leverage that the targeting of Covid-19 post-lockdown policies at reductions of non-local transmission may provide to global, national, or regional policy makers.

## 2.2 Interventions

In epidemiological models effects of both general and targeted interventions on disease spread have been studied [23]. General interventions such as social distancing and school closures aim to bring down overall infection probabilities or those within and between demographic subgroups [10]. Targeted interventions seek to identify high-risk individuals: Antiviral treatment and household isolation of identified cases, prophylaxis and quarantine of household members. We propose a different kind of targeting that is not aimed at specific *nodes* but at high-impact *edges* of a network.

A challenge faced by contemporary policy makers is when and how to ease interventions. How can a second wave be minimized while at the same time preventing enormous economic costs? It is well known that when a lockdown is lifted, a virus tends to re-appear [24]. Therefore it is of paramount importance to find ways to regain some form of normal life (alleviating lockdown) while at the same time preventing the virus from going viral again. The main idea proposed here is that restricting certain high-risk interactions within the social network may be a better strategy than to restrict those of an entire population. 'Long-distance' ties represent interaction between individuals that are distant to each other in a network. Typically this means they are also physically distant, i.e. think of a truck driver that delivers goods to a company on the other side of the country or individuals traveling by plane that encounter each other at airports and in airplanes where social distancing is difficult or next to impossible. Small-world models suggest that long-distance ties greatly accelerate the speed of transmission. Long-range ties stemming from infected individuals allow disease to start spreading in distant other localities and much more often lead to not-yet-infected individuals and regions. At a global level, long ties predominantly involve international highways and airline transportation. Topological properties of airline transportation networks can explain patterns in viral disease spread worldwide [25, 12]. At a national level, long ties pertain to mobility through major roads and trains between cities and at a regional level to commuting and local delivery services.

# 3 Model

## 3.1 SEIR model

We follow the standard SEIR model that transitions individuals through four stages of an infectious disease. In the SEIR model [26] a population is divided into four compartments of Susceptible, Exposed, Infected, and Recovered

$$\begin{aligned} \frac{dS}{dt} &= -\beta \frac{I}{N} S \\ \frac{dE}{dt} &= \beta \frac{I}{N} S - \alpha E \\ \frac{dI}{dt} &= \alpha E - \gamma I \\ \frac{dR}{dt} &= \gamma I \end{aligned}$$

Here we ignore demographic changes, i.e., birth and death are not accounted for: the total population $N = S + E + I + R$ remains constant. The parameters $\alpha, \beta, \gamma$ describe the transmission rates between the states, where $\beta$ depends on the number of social contacts, while $\alpha$ and $\beta$ are the reciprocal values of the incubation period and the average duration of the infection. The SEIR model has been applied in various studies of the COVID-19 outbreak [27, 28, 10]. A standard range of the parameters is $\beta = 1.5 - 3, \alpha = 0.2 - 0.3, \gamma = 0.1 - 0.3$, [29, 30, 10]. We fix our parameters within these ranges at $\alpha = 0.217$, $\beta = 2$, and $\gamma = 0.154$.

| Parameter | Value |
|---|---|
| $\alpha$ | $1/4.6 = 0.217$ |
| $\beta$ | $0.1 \cdot k = 2$ |
| $\gamma$ | $1/6.5 = 0.154$ |
| $N$ | 10000 |
| $I(0)$ | 1 |
| $k$ | 20 |
| $p$ | 0.1 |

Table 1: Parameter settings.

## 3.2 Social network

In a small-world network ties are either long or short. The network is described by two parameters $k, p$, where $k$ is the number of ties per node and $p$ is the fraction of long ties. In our model, the population $N$ is connected through a small world network. Each node is in one of the four SEIR states. The time step is one day. In this model, the nodes are individuals, but it can also be used on a larger geographic scale to describe the outbreak in countries (nodes are cities) or continents (nodes are countries). For purposes of illustration a small example network with $N = 100$, $k = 10$, and $p = 0.05$ is shown in Figure 1. In the simulations we fix $N = 10000$, $k = 10$, and $p = 0.1$. Results seem robust to reasonable changes in these parameters.

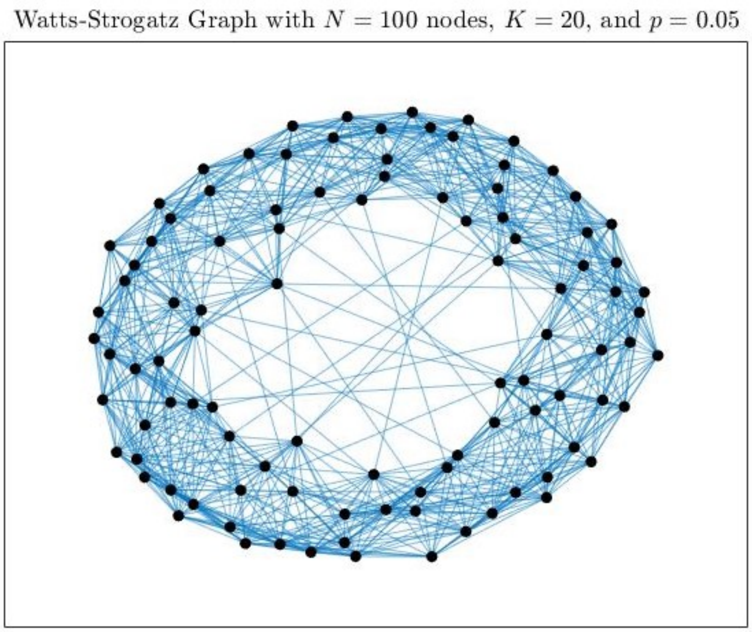



Figure 1: An example of a small-world graph.

### 3.3 Interventions

We model a scenario in which the population goes into lockdown three weeks after its first Covid-19 infection on day 1. The initial per-contact transmission probability is 0.1 for both short- and long-range ties, $r_{long} = r_{short} = \beta/k = 0.1$. The lockdown is modeled as a global intervention that reduces on day 25 the per-contact probability of disease transmission, $r_{long} = r_{short} = 0.01$. A second, targeted intervention occurs on day 100, when per-contact transmission through short-range ties goes back to normal, $r_{short} = 0.1$, but transmission through long-range ties, $r_{long}$, remains limited to a degree that we systematically vary. We also study a version where $r_{short}$ on day 100 is set at 0.05, reflecting maintenance of some forms of social distancing after lockdown. We thus model a scenario in which policy makers rely heavily or entirely on long-range transmission blockage to reduce the second wave of Covid-19 infections.

# 4 Results

Our results are preliminary, with an eye to the urgency of the present epidemic. Subsequent work may further explore robustness.

## 4.1 Spatial distribution of Covid-19

We seek to validate our model by comparing empirical to simulated distributions of Covid-19 spread. Figure 2 shows the spatial distribution of Covid-19 cases on April 6, 2020 at three scales: countries, regions in Italy, and provinces in Italy (Source: gisanddata.maps.arcgis.com). Figure 2 also shows the spatial distribution of Covid-19 spread in our model after 50 days, 25 days into lockdown. To this end we arbitrarily divided the ring lattice of $n = 10{,}000$ nodes into 100 regions of 100 nodes each. Both empirical observations and simulations appear a good fit to the exponential distribution, with standard deviation roughly equal to the mean.

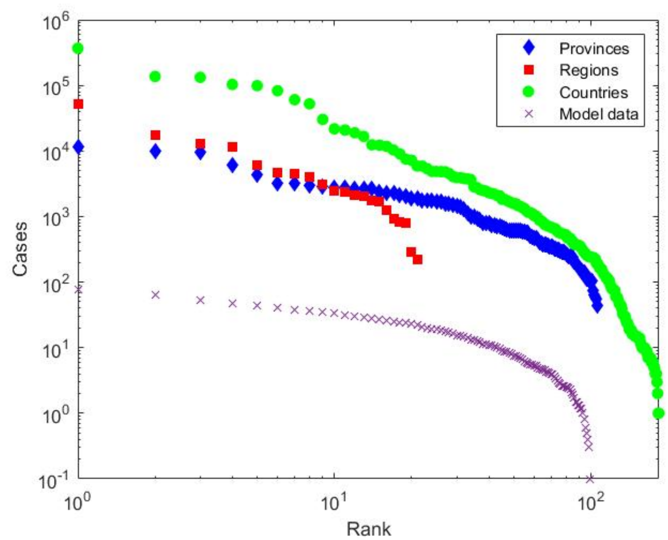


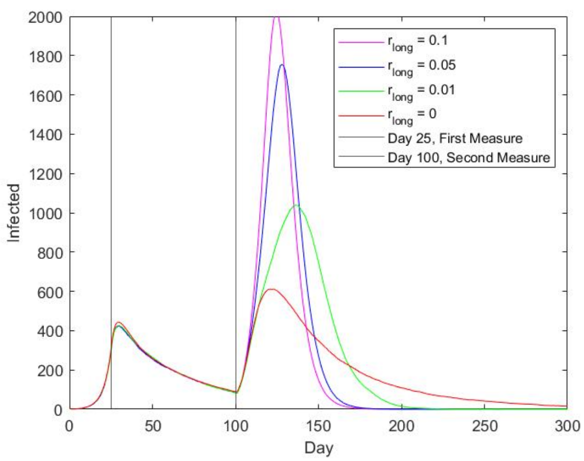

Figure 2: Number and rank of Covid-19 cases across countries, regions (Italy), provinces (Italy) on April 6, 2020, and across 100 equally-sized regions of the simulated social network.

## 4.2 Second wave of Covid-19

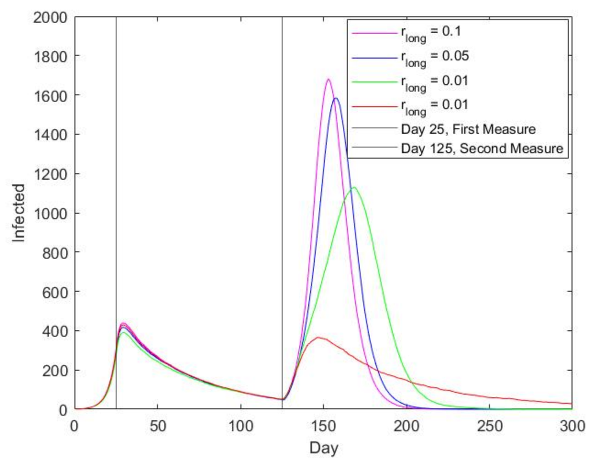
### 4.2.1 Peak

Figure 3a varies the per-contact transmission probability $r_{long}$ after the lockdown on local ties is entirely lifted. When restrictions on long ties are also lifted so that $r_{long}$ goes back to its original level of 0.1, the peak of the second wave vastly exceeds that of the first wave. Reductions in $r_{long}$ flatten the curve. At $r_{long} = 0$, the second curve is only modestly higher than the first, even though at $p = 0.1$ 90 percent of all ties are fully active.

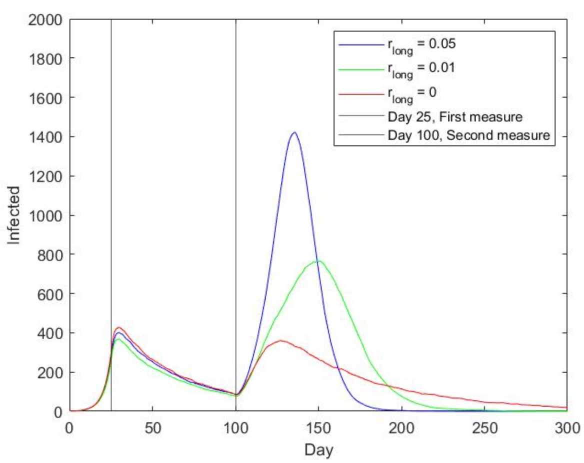
Figure 3b shows that comparable effects of suppressing long tie transmission are obtained when lockdown release is delayed by another 25 days.



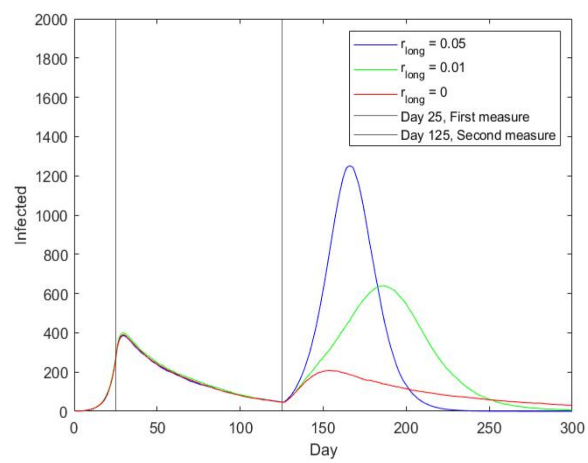

(a) Lockdown removed on day 100, $r_{short} = 0.1$




(b) Lockdown removed on day 125, $r_{short} = 0.1$




(c) Lockdown removed on day 100, $r_{short} = 0.05$




(d) Lockdown removed on day 125, $r_{short} = 0.05$

Figure 3: Effect of varying long-range transmission probability $r_{long}$ after lockdown removal on second wave peak. $r_{long}$ and $r_{short}$ start at 0.1 on day 1, and switch to 0.01 on day 25. On day of lockdown removal, $r_{short}$ is set to 0.1 or to 0.05.

Figure 3c studies the same scenario except that on day 100 $r_{short}$ is kept at 0.05 (e.g. some social distancing measures are left in place). Without further restrictions on long-range ties, $r_{long} = 0.05$, a sizeable second peak occurs. With $r_{long}$ reduced, the curve is substantially flattened and at maximal suppression of long ties, the second peak is lower than the first. Note that the blue peak in figure 3c, where $r_{short} = 0.05$, is only mildly lower than the blue peak in figure 3a, where $r_{short} = 0.10$. In other words, reducing transmission in short ties is much less effective than in long ties, even though the former are much greater in number.

Figure 3d shows that when a partial lockdown release is delayed by another 25 days, effects of suppressing long tie transmission are comparable.

It is important to note that *strong* reductions in long tie transmission are particularly effective. Marginal effects of decreases in $r_{long}$ are increasing. This concords with studies showing that international traffic constraints are particularly effective when severe [12].

### 4.2.2 Spatial concentration

Post-lockdown flare-ups are more easily controlled with geographically focused efforts when they remain local longer. Economic and social costs of control measures are then also lower. We study the spatial concentration of Covid-19 outbreaks by measuring the number of components of the subgraph of infected nodes and short edges. Figure 4 compares the number of components for the scenario where lockdown is completely lifted on day 100, $r_{long} = r_{short} = 0.1$ with the alternative scenario where short ties are fully normalized, $r_{short} = 0.1$, while long-range transmission is maximally repressed, $r_{long} = 0$. The latter scenario is characterized by a smaller number of components during the second wave.

## 5 Discussion and Policy

Our model simulations explored spatially differentiating policies in which non-local spread of Covid-19 is severely inhibited. Our results show that reductions of transmission levels in long-distance ties are more effective than reductions in short-distance ties in curbing the spread of Covid-19. What policies could constrain long-range transmission? Medical testing and mobility-tracking apps may be targeted specifically at transport, travel, and delivery. Perhaps medical testing and / or mobility tracking should be encouraged or required for flight, use of highways, trains, regional bus lines and for individuals with jobs in the transport and delivery sector. Self-isolation after exposure of such individuals may perhaps be more stringently enforced. What helps is that long-range ties are relatively sparse, so resources may be focused on a limited number of individuals or activities. That said, our result show that effects are particularly strong when transmission through long-range ties is not just reduced but largely eliminated. The logistical, technological and ethical challenges of geo-

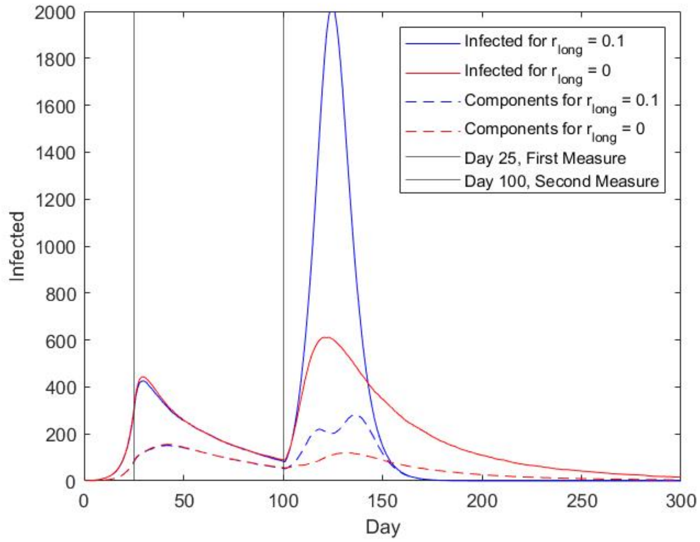



Figure 4: Effect of varying long-range transmission probability $r_{long}$ after lockdown removal on the spatial concentration of novel outbreaks. Concentration is measured as the number of components in the subgraph of infected nodes. $r_{long}$ and $r_{short}$ start at 0.1 on day 1, and switch to 0.01 on day 25. On day 100, $r_{short}$ is set back to 0.1 and $r_{long}$ to either 0.1 or 0.

graphic targeting in location tracking, testing, and police enforcement require further interdisciplinary study.

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