

Mobility-guided Modeling of the COVID-19 Pandemic in Metro Manila

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Coronavirus disease 2019 (COVID-19) is a novel respiratory disease first identified in Wuhan, China, that is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). To better understand the dynamics of the COVID-19 pandemic in the Philippines, we have used real-time mobility data to modify the DELPHI epidemiological model recently developed at the Massachusetts Institute of Technology (MIT) and to simulate the pandemic in Metro Manila. We have chosen to focus on the National Capital Region (NCR), not only because it is the nation's demographic heart where over a tenth of the country's population lives, but also because it has been the epidemiological epicenter of the Philippine pandemic. Our UST CoV-2 model suggests that the government-imposed enhanced community quarantine (ECQ) has successfully limited the spread of the pandemic. It is clear that the initial wave of the pandemic is flattening, though suppression of viral spread has been delayed by the local pandemics in the City of Manila and Quezon City. Our data also reveals that replacing the ECQ with a general community quarantine (GCQ) will increase the forecasted number of deaths in the nation's capital unless rigorous tracing and testing can be implemented to prevent a second wave of the pandemic.

Keywords: COVID-19 model, DELPHI model, Manila, mobility-guided, Philippines

INTRODUCTION

COVID-19 is a novel respiratory disease first identified in Wuhan, China, that is caused by SARS-CoV-2 (Guan *et al.* 2020; Xie *et al.* 2020; Zhu *et al.* 2020). With widespread human-to-human transmission, the virus is highly contagious, and the COVID-19 pandemic is now of global concern (Burki 2020; Paules *et al.* 2020).

On 30 Jan 2020, the Department of Health of the Philippines (DOH) reported its first case of COVID-19 in the country. She was a 38-year-old female Chinese

national who had traveled to the Philippines from Wuhan *via* Hong Kong. The first case of local transmission was confirmed on 07 Mar 2020, with the first death due to local transmission reported on 11 Mar 2020. As of 21 May 2020, there have been 13,434 confirmed cases and 846 deaths from COVID-19 reported by the DOH throughout the archipelago.

To contain the COVID-19 pandemic, the national government of the Philippines imposed an Enhanced Community Quarantine (ECQ) on the country's National Capital Region (NCR), also known as Metro Manila, on 15 Mar 2020, which was extended to the entire island

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of Luzon and its 55 million inhabitants the following day. The ECQ imposed a strict stay-at-home order, banned all public gatherings, suspended all mass public transportation, and closed all non-essential business establishments. On 24 Apr 2020, the ECQ was extended in the NCR and several other provinces and municipalities that were considered high-risk for COVID-19. On 15 May 2020, Metro Manila and several surrounding regions were placed on a modified Enhanced Community Quarantine (MECQ) that is to stay in place until 31 May 2020. At that time, if conditions permit, the NCR is expected to move to a more relaxed GCQ.

Numerous mathematical models have been developed to understand the global COVID-19 pandemic (Adam 2020; Currie *et al.* 2020; Holmdahl and Buckee 2020). To better understand the dynamics of the local pandemic in the Philippines, we have used real-time mobility data to adapt the DELPHI (Differential Equations Leads to Predictions of Hospitalizations and Infections) epidemiological model recently developed at MIT (Bertsimas *et al.* 2020) to the pandemic in Metro Manila. The DELPHI model is a standard SEIR (susceptible-exposed-infected-recovered) model with additional features, including under-detection and differentiated government intervention, that are particularly helpful for modeling this current pandemic. Finally, it uses a machine-learning algorithm to determine the best-fit epidemiological parameters from the historical data of death counts and detected cases. The current SEIR models for the COVID-19 pandemic in the Philippines do not have these enhancements (David *et al.* 2020).

We have chosen to focus on the NCR, not only because it is the nation's demographic heart where over a tenth of the country's population lives, but also because it has been, by far, the epidemiological epicenter of the Philippine pandemic: As of 21 May 2020, 8,659 cases (64% of the country's total) and 621 deaths (73%) have been reported in Metro Manila.

Our UST CoV-2 mobility-guided enhanced SEIR model suggests that the lockdown measures of the ECQ have successfully limited the spread of the pandemic in the NCR. It is clear that the initial wave of the pandemic is flattening, although suppression of viral spread has been delayed by the local pandemics in Quezon City and the City of Manila. Our model also reveals that releasing these measures will increase the forecasted number of deaths in the nation's capital unless rigorous tracing and testing can be implemented to prevent a second wave of the pandemic.

MODELING METHODS

The DELPHI epidemiological model recently developed at MIT is a compartmental model that is based on the successful SEIR models that have been used to simulate numerous past epidemics (Bertsimas *et al.* 2020). However, it also accounts for the underdetection of cases, which is particularly important when a community is unable to adequately test for the disease during the pandemic, and for possible societal-governmental responses to contain the spread of the contagion. Both enhancements are essential for robust modeling of the current COVID-19 pandemic.

To model the underdetection of cases, the DELPHI model separates the target population into 11 possible categories during the pandemic: Susceptible (S), Exposed (E), Infected (I), Undetected Recovered (AR), Undetected Dead (AD), Detected Hospitalized Recovered (DHR), Detected Hospitalized Dead (DHD), Detected Quarantined Recovered (DQR), Detected Quarantined Dead (DQD), Recovered (R), and Dead (D). The novel buckets not included in classic SEIR models allow the model to simulate populations at the outset of a pandemic where testing is being ramped up. The model also includes a parameter (p_d) for the percentage of detected cases of infection detected that allows it to incorporate varying testing capacities for the target population. A list of the differential equations that drive the DELPHI model – as well as its initial conditions, parameters, and variables – are included in the supplemental information.

To model the societal-government response, the DELPHI model includes a multiplier for the rate of infection in the form of a smooth parametric nonlinear arctan function:

$$\gamma(t) = \frac{2}{\pi} \arctan\left(-\frac{t-a}{b}\right) + 1 \quad (1)$$

Parameters a and b can be varied to model a wide range of policies – including social distancing, stay-at-home policies, and lockdowns ($a > 0$ and $b > 0$).

Finally, in the original DELPHI model, key parameters for COVID-19 were fixed using a meta-analysis conducted by the MIT COVIDAnalytics team and epidemiological parameters were fitted to historical death counts and detected cases using a machine learning algorithm that best fits these parameters to the observed data.

To simulate the COVID-19 pandemic in Metro Manila, we modified the DELPHI model in four ways:

First, real-time mobility data obtained from Apple, Inc. for driving, walking, and transit on 21 May 2020 (<https://www.apple.com/covid19/mobility>) revealed that the lockdown in Metro Manila that began on 15 Mar 2020, resulted in a dramatic and near-immediate drop in mobility over the course of several days. A graph of the changes in mobility in

the NCR obtained by first averaging the three mobility data sets provided by Apple, Inc. – driving, walking, and transit – for each date, and then calculating a seven-day running average of these means is shown in Appendix Figure I. Therefore, to better simulate the initial period of the local pandemic in Metro Manila, we replaced the original smooth parametric nonlinear arctan function adopted by the MIT team with an almost step-like function that would be fitted to the historical COVID-19 pandemic data from the DOH for the NCR using a modified machine learning algorithm.

Our replacement is a function $\gamma(t)$, which can change fast within a few days between constant values. The value of $\gamma(t)$ is 1 at the beginning of the COVID-19 outbreak. Two days before the optimized median day of action t_a the function $\gamma(t)$ starts dropping rapidly to the optimized level of action L_a . This reduces to the effective reproduction number:

$$R(t) = \alpha\gamma(t) / r_d$$

where α is the infection rate and r_d is the detection rate that moves an individual out of the I compartment, as expected during community quarantine. The level of action L_a is reached two days after t_a . During this four-day transition, the $\gamma(t)$ function connects the two constant levels with a cubic spline:

$$\gamma(t) = L_a + \frac{1-L_a}{2} \left(1 - \frac{3(t-t_a)}{2t_1} + \left(\frac{1}{2}\right) \left(\frac{t-t_a}{t_1}\right)^3 \right) \quad (2)$$

for $t_a - t_1 < t < t_a + t_1$ with the transition time $t_1 = 2$ days. The $\gamma(t)$ function is equal to L_a during the community quarantine. In our view, this novel multiplier developed with mobility data in mind allows us to better simulate the dramatic lowering of the rate of infection that is expected during the initial days of the ECQ because of the dramatic decrease in mobility. Human mobility proxies have been used in the past to understand the spread of infectious diseases, including COVID-19 (Tizzoni *et al.* 2014).

Next, the Apple Mobility data revealed that the mobility of communities in Europe that were put into relatively lenient lockdowns recovered linearly from the minimum achieved immediately after quarantines were established. Three representative curves from Austria, Germany, and Norway (obtained as above) by first averaging the three mobility data sets provided by Apple, Inc. – driving, walking, and transit – for each date and then calculating a seven-day running average of these means are shown in Appendix Figure II. It is likely that the shape of this recovery reflects both the gradual easing of the lockdowns and the hesitant movements of a quarantined population that remains wary of the disease. We, therefore, chose to model the lifting of the community quarantine in Metro Manila with a smooth cubic spline interpolation function

that allows us to transition the multiplier of the infection rate from the lockdown level, L_a , to a higher level, between L_a and 1:

$$\gamma(t) = L_a + \frac{\sigma(1-L_a)}{2} \left(1 + \left(\frac{3(t-t_b)}{2t_2}\right) - \left(\frac{1}{2}\right) \left(\frac{t-t_b}{t_2}\right)^3 \right) \quad (3)$$

for $t_b - t_2 < t < t_b + t_2$. We considered two scenarios: a smooth increase with a transition time t_2 of 7 days where t_b corresponds to 07 Jun 2020, and a very smooth increase with a transition time t_2 of 15 days where t_b corresponds to 15 Jun 2020. The $\gamma(t)$ function is equal to the constant $L_a + \sigma(1 - L_a)$ after this transition. In order to study the effect of different σ values, σ was increased from 0 to 1 in steps of 0.1. A value of 0 for σ means that $\gamma(t)$ stays at the level L_a associated with the original lockdown, whereas a value of 1 for σ means that $\gamma(t)$ returns to the initial value 1. That is, the value of σ quantifies the effect of the lifting of the lockdown, which depends on how much the mobility of the people changes. We eventually chose to focus our analysis on a two-week period of transition (t_2 is 7 days) from the ECQ to GCQ because we believe that it would take two weeks for people to adjust to the new more-relaxed quarantine.

Third, we replaced the original machine learning algorithm in the DELPHI model. The variables of the modified model used in this study were optimized by minimizing a function $f(\alpha, t_a, L_a, r_{dth}, p_{dth}, k_1, k_2)$ of initially seven variables while respecting the upper and lower bounds specified for them. The variables are the infection rate α , the median day of action t_a , the level of action L_a , the rate of death r_{dth} , the probability of mortality p_{dth} , as well as the internal parameters k_1 and k_2 for optimizing the initial conditions (see Appendices section). This function is a measure of the distance between the predictions of the DELPHI model and the historical data of death counts and detected cases. The function was minimized with the aid of the dual_annealing algorithm of the Python module SciPy, which tries to find the global minimum of a function with upper and lower bounds specified for the variables. This algorithm performed best among the minimization algorithms we tested. To reduce the number of variables that need to be optimized from seven to six, we fixed the infection rate α to $2.2r_d$. This corresponds to a basic reproduction number $R_0 = \alpha/r_d$ of 2.2, which is a published estimate for the R_0 for SARS-CoV-2 (Li *et al.* 2020). The value of α was fixed by specifying upper ($2.2r_d + 0.000000001/d$) and lower ($2.2r_d - 0.000000001/d$) bounds, which are just slightly above and below $2.2r_d$. The software accompanying this paper can be found on Github.com with the following DOI: 10.5281/zenodo.3953074.

Finally, we specified several of the epidemiological parameters of the original DELPHI model to better reflect the local pandemic in Metro Manila. The values for the clinical and epidemiological parameters used in our model

Table 1. Parameters for the UST CoV-2 model for the pandemic in Metro Manila.

Model parameter	Value	Source
Median time to leave incubation	5 d	Bertsimas <i>et al.</i> (2020)
Median time to recovery without hospitalization	10 d	Bertsimas <i>et al.</i> (2020)
Median time to detection	2 d	Bertsimas <i>et al.</i> (2020)
Median time to recovery in hospital	15 d	Bertsimas <i>et al.</i> (2020)
Ratio of recoveries to deaths	6:1	worldometers.info
p_d for the Philippines (% infected cases detected)	0.02	Bommer and Vollmer (2020)
p_h for Metro Manila (% detected cases hospitalized)	0.10	doh.gov.ph/covid19tracker
Population of Metro Manila	13,923,452	worldpopulationreview.com

are displayed in Table 1. Additional parameter values and the initial conditions for our modeling efforts are provided in the Appendices section.

All historical data for the pandemic in the NCR was obtained from the COVID-19 Tracker website maintained by the DOH (<https://ncovtracker.doh.gov.ph/>). We have noticed that this historical data set is constantly being revised to reflect the results of ongoing validation. Our model used the confirmed values that were available on 21 May 2020 to generate the results described in this paper. Data from New York City was obtained from the website of the New York City Department of Health (<https://www1.nyc.gov/site/doh/covid/covid-19-data.page>).

RESULTS AND DISCUSSION

Impact of the ECQ in Metro Manila

There is evidence that social distancing practices and community-wide lockdowns have been effective at blunting the COVID-19 pandemic and preventing health systems from being overwhelmed in different countries around the world (Flaxman *et al.* 2020; Haushofer and Metcalf 2020; Hsiang *et al.* 2020). As shown in Figure 1, our UST CoV-2 model suggests that the government-imposed ECQ has also successfully limited the impact of the pandemic in Metro Manila by significantly lowering the total number of COVID-19 cases and the total number of deaths.

As a point of comparison, Metro Manila and New York City – two metropolitan areas with comparable

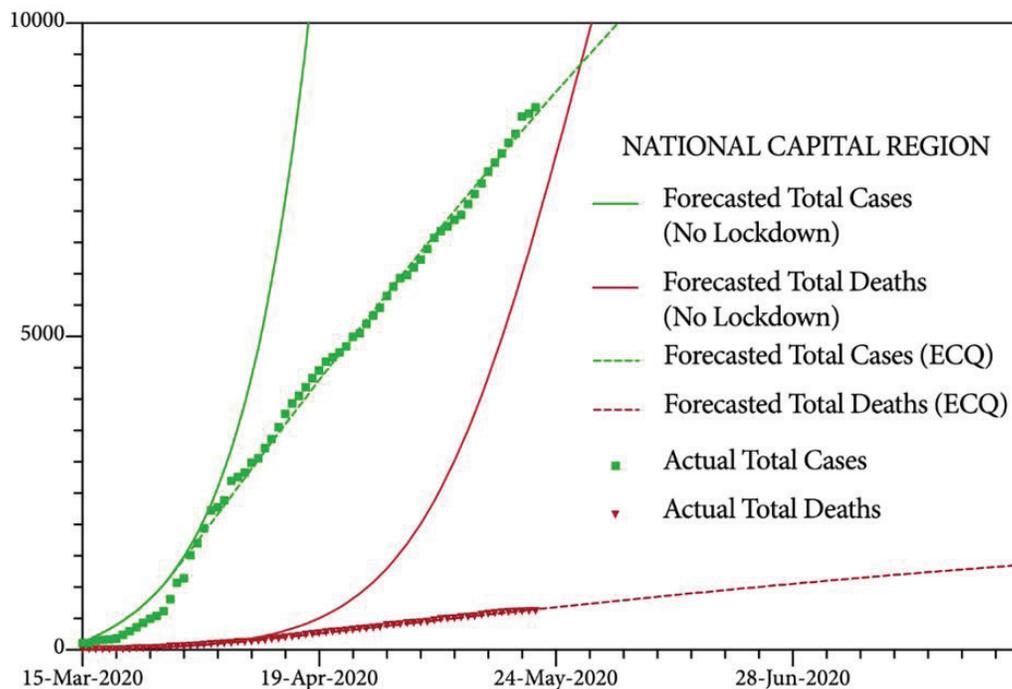


Figure 1. Modeling the impact of the ECQ on the COVID-19 Pandemic in Metro Manila. Forecasted estimates of total COVID-19 cases and total deaths for NCR without a lockdown and with the ECQ compared to the data provided by the DOH.

populations – recorded their first deaths from community spread of COVID-19 on 11 Mar 2020 and 13 Mar 2020, respectively. However, Metro Manila entered lockdown on 15 Mar 2020, while New York City waited one more week to enter its lockdown on 20 Mar 2020. As of 21 May 2020, Metro Manila reported 621 total deaths from COVID-19 while New York City confirmed 16,232 total deaths. It appears that the early implementation of the ECQ has been able to spare the lives of thousands of residents of the NCR.

Our results also suggest that the first wave of the pandemic is receding. As shown in Figure 2, the number of forecasted active cases peaked in early May and is gradually declining. Currently, there is no evidence for a second wave of the pandemic. Note that we decided not to compare this modeled curve of forecasted active cases with the data for active cases provided by the DOH of the Philippines because we believe that the number of recovered cases is under-reported in this data set amid delays in the validation process established by the DOH: there are cases of COVID-19 patients who were listed as having mild symptoms whose health status remains unknown two months after their initial diagnosis. This is medically inexplicable, and we believe that it is better explained by gaps in the data collection during this time of the pandemic.

Though the curve for the pandemic in the NCR is flattening gradually, the flattening is not dramatic. In fact, it is clear that the ECQ is struggling to suppress the pandemic, *i.e.*

to drive the number of infected cases down to zero. At this rate, the model predicts that the total number of cases in Metro Manila will continue to gradually increase and will not plateau for many months, although the forecasted number of active cases will also be decreasing. If the current quarantine measures are maintained, the forecasted number of active cases of COVID-19 will not fall below 1,000 cases until early-September.

To uncover possible reasons for this less-than-dramatic slowing of viral spread, we modeled the local pandemics in the five cities within Metro Manila that have the largest numbers of cases of COVID-19. These are Quezon City and the cities of Makati, Mandaluyong, Manila, and Parañaque. These five cities together represent over half of the total number of COVID-19 cases in the NCR.

Our modeling reveals that the efficacy of efforts to suppress the pandemic has varied widely throughout the NCR. As shown in Figure 3, cities like Makati, Mandaluyong, and Parañaque have been more successful at suppressing the community spread of COVID-19 than Manila or Quezon City. If the current quarantine measures are maintained, the total number of cases is forecasted to plateau by mid-July in Mandaluyong, by early August in Makati, and by September in Parañaque. However, the same cannot be said for the latter two cities where the total number of cases is forecasted to gradually keep increasing for many months, although the forecasted number of active cases will also be decreasing.

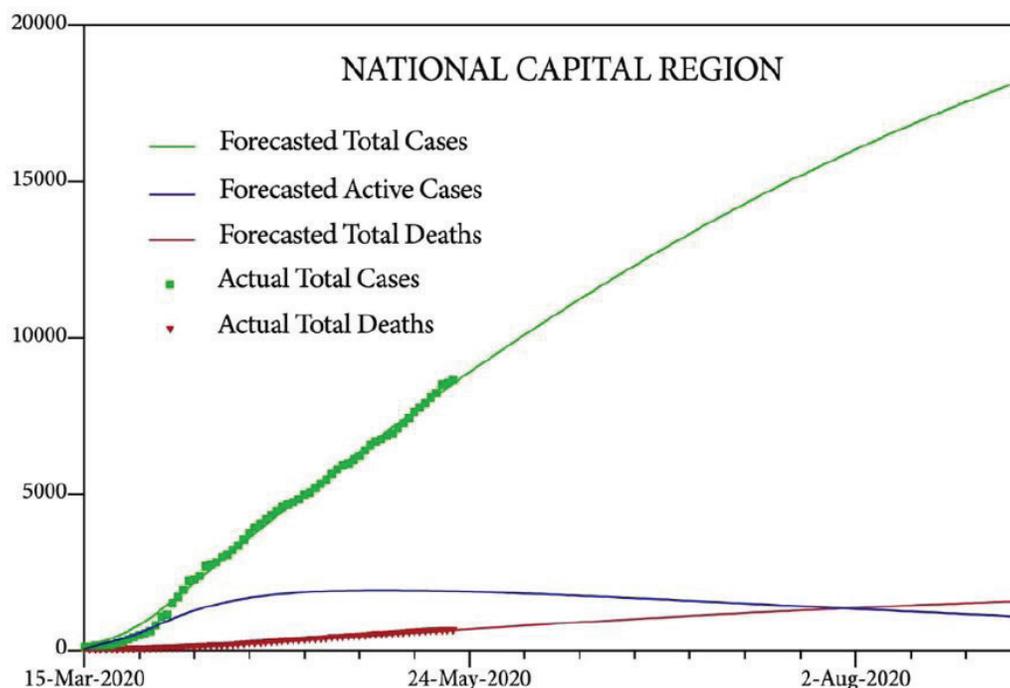


Figure 2. Modeling the COVID-19 Pandemic under ECQ in Metro Manila. Forecasted estimates of total COVID-19 cases, total active cases, and total deaths for NCR with the ECQ compared to the data provided by the DOH.

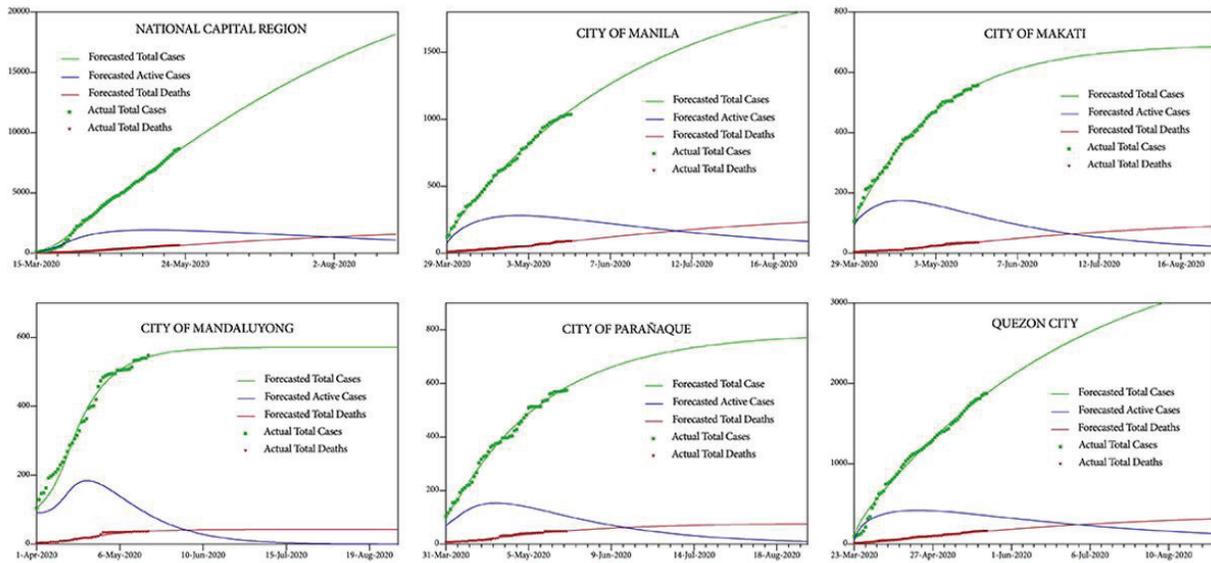


Figure 3. Modeling the COVID-19 Pandemic under ECQ in individual component cities of Metro Manila. Forecasted estimates of total cases, total active cases, and total deaths for NCR and the five component cities with the highest recorded cases of COVID-19 with the ECQ compared to the data provided by the DOH.

It is not clear why the ECQ has not been as effective in both the City of Manila and Quezon City as it has been in their neighboring municipalities. Although Manila is the densest city in the world, Quezon City is not the second densest in the NCR. Thus, the different effects of the ECQ are unlikely to be explained by appealing to population density alone. Nonetheless, both these urban areas have experienced several-fold higher infections than the other component cities in the capital region. Thus, it is not unreasonable to posit that the dynamics of the COVID-19 pandemic in Metro Manila are being driven by both local pandemics. It suggests that public health authorities should increase their efforts to contain the pandemic in the NCR in these two cities.

Impact of Easing the ECQ in Metro Manila

To model the impact of replacing the ECQ with the GCQ, we reran our model assuming that the ECQ would be eased on 01 Jun 2020 and that it would take 2 weeks for people to adjust to the new more-relaxed quarantine. As explained above, we had observed that the mobilities of communities released from lockdowns in Europe recovered in a linear fashion. Therefore, we chose to model the easing of the ECQ in Metro Manila with a smooth cubic spline interpolation function that would increase the modeled infection rate at a relatively linear rate once the strict community lockdown is lifted. Since the proposed GCQ (<http://www.covid19.gov.ph/ecq-gcq-guidelines/>) will seek to limit the mobility of the relatively young (< 21 years old) and the relatively old (> 60 years old), two populations who together constitute about half

of the number of the Filipino people nationwide (<https://www.populationpyramid.net/Philippines/2019/>), we interrogated the effect on the pandemic of increasing the infection rate by half of the amount that it decreased during the ECQ, *i.e.* a post-ECQ recovery rate of 50% in the infection rate that would mirror the expected post-ECQ recovery rate of 50% in the mobility of the residents of the NCR.

As shown in Figure 4, it is clear that replacing the ECQ with a GCQ will increase the forecasted number of infected cases and deaths in Metro Manila. If the post-ECQ infection rate is allowed to recover by half of the amount it decreased during the lockdown over a two-week period, then our model predicts that the total number of infected cases of COVID-19 will grow from 15,952 to 35,235 and that the total number of deaths will rise from 1,356 to 2,415 by 01 Aug 2020.

It is important to emphasize that these increases in both total cases and deaths are not inevitable. They can be offset with a rigorous tracking, testing, and tracing program that seeks to limit community spread by breaking chains of viral transmission (Cheng *et al.* 2020; Hellewell *et al.* 2020). Given the observation that typically, only 20% of a population contributes to at least 80% of the potential to transmit infectious disease (Woolhouse *et al.* 1997; Endo *et al.* 2020), we recommend that tracking, testing, and tracing programs in Metro Manila focus their efforts on limiting the impact of superspreading events that are associated with both explosive growth early in an outbreak and sustained transmission in later stages (Frieden and Lee 2020).

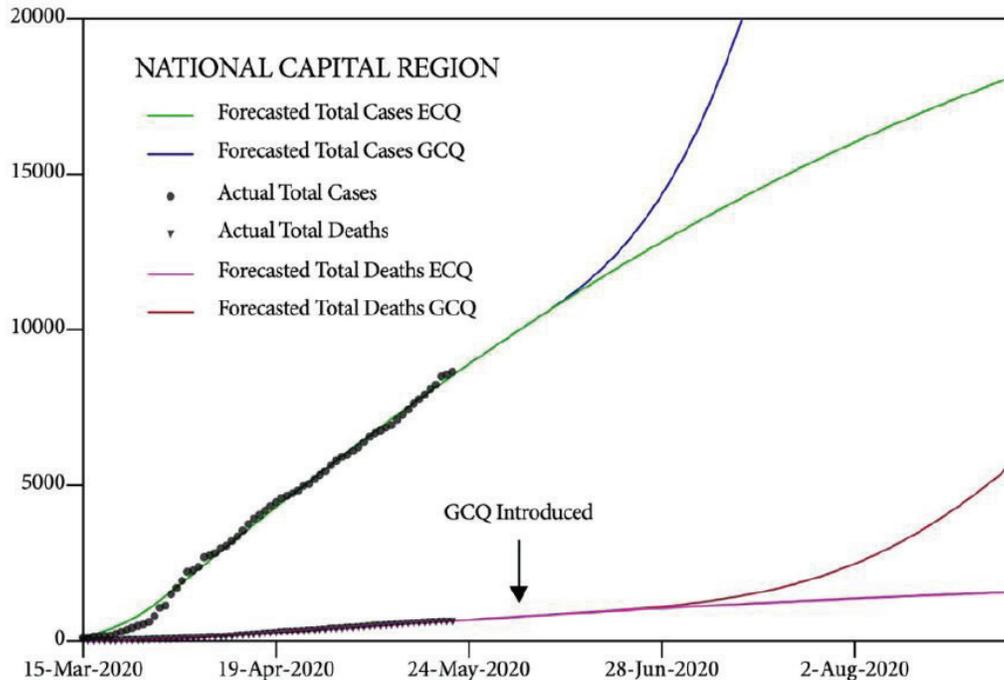


Figure 4. Modeling the impact of the GCQ in Metro Manila from 01 Jun 2020. Forecasted estimates of total COVID-19 cases, total active cases, and total deaths for NCR for the ECQ and GCQ compared to the data provided by the DOH.

How much testing and tracing capacity will be needed in Metro Manila to keep the pandemic at bay? A team of scholars at the Edmond J. Safra Center at Harvard University has recently published recommendations for communities of different sizes and at different stages in controlling their pandemics (Allen *et al.* 2020). They propose that every municipality with a moderate infection rate, *i.e.* with less than 1% prevalence of the active virus in its population – for the most part, the NCR appears to fulfill this criterion – should hire sixty teams of five tracers for every death per day that they observe in their community, and maintain a testing capacity of 2,500 tests for every death per day.

On 22 May 2020, the seven-day running average of deaths per day recorded in Metro Manila was six deaths per day. This means that at this stage of the pandemic, according to the recommendations of the Harvard team, the NCR would need a testing capacity of 15,000 tests per day and 1,800 contact tracers working in call centers scattered throughout the region to control its local pandemic. Geographic distribution of this testing and contact tracing capacity should correspond to the severity of the local pandemics in each of the cities of Metro Manila, with a particular focus on the City of Manila and Quezon City.

In sum, although they were necessary to squash the initial wave of the COVID-19 pandemic, community-wide lockdowns are not sustainable in the long run because of

their grave socio-economic impact, especially on the lives of the poor (Nicola *et al.* 2020). Our modeling suggests that the government-imposed ECQ has successfully limited the spread of the pandemic in Metro Manila. It has given the Philippine government precious time to ramp up the social and medical infrastructure that will be needed to mitigate and contain the virus for the foreseeable future until a vaccine is developed. Resources must now be invested to increase testing and contact tracing capacity to prevent future outbreaks of COVID-19 and to increase the capacity of the Philippine health care system, including sufficient supplies of PPE so that it will be able to deal with a possible second wave of the pandemic later this year.

Limitations of our Study

Our study has two primary limitations. First, we did not include the effect of modifying the ECQ in Metro Manila on 15 May 2020. If this change in the lockdown has any effects on the local pandemics, we would not expect these to manifest themselves until 14 days after the modification, which is beyond the scope of this present study that was completed on 21 May 2020. Second, our model is only as good as the data set upon which it relies. Since there are credible news reports in the Philippines that suggest that the DOH data set is incomplete because of a delay in the validation process (Sabillo 2020), it is not clear if the unavailable data would alter our modeling results.

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APPENDICES

Optimized Variables of the DELPHI Model

- α # Infection rate was fixed to $2.2 r_d$. That is, a value of 2.2 was assumed for the basic reproduction number $R_0 = \alpha/r_d$. This was done to reduce the number of parameters that need to be optimized.
- t_a # Median day of action
- L_a # Level of action (replaces the rate of action r_s in the original DELPHI model)
- r_{dth} # Rate of death
- p_{dth} # Probability of mortality
- k_1 # Internal parameter 1
- k_2 # Internal parameter 2

Bounds for the Variables

- α Bound within the very narrow interval [$2.2 r_d - 0.000000001/\text{days}$, $2.2 r_d + 0.000000001/\text{days}$]
- t_a Bound within the interval [0.01, 0.9]
- L_a Bound within the interval [0.01, 0.9]
- r_{dth} Bound within the interval [0.01, 0.5]
- p_{dth} Bound within the interval [0.01, 0.25]
- k_1 Bound within the interval [0.1, 10.0]
- k_2 Bound within the interval [0.1, 10.0]

Fixed Rates

- $r_i = \ln(2) / 5 \text{ days}$ # Rate of infection leaving incubation phase
- $r_d = \ln(2) / 2 \text{ days}$ # Rate of detection
- $r_{ri} = \ln(2) / 10 \text{ days}$ # Rate of recovery not under hospitalization
- $r_{rh} = \ln(2) / 15 \text{ days}$ # Rate of recovery under hospitalization
- $r_{rv} = \ln(2) / 10 \text{ days}$ # Rate of recovery under ventilation

Fixed Probabilities

- $p_v = 0.25$ # Probability of ventilation
- $p_d = 0.02$ # Probability of infection case detection
- $p_h = 0.1$ # Probability of detected cases hospitalization

Equations on Main Variables

- $dS(t)/dt = -\alpha \gamma(t) S(t) I(t)/N$
- $dE(t)/dt = \alpha \gamma(t) S(t) I(t)/N - r_i E(t)$
- $dI(t)/dt = r_i E(t) - r_d I(t)$
- $dAR(t)/dt = r_d (1 - p_{dth}) (1 - p_d) I(t) - r_{ri} AR(t)$
- $dDHR(t)/dt = r_d (1 - p_{dth}) p_d p_h I(t) - r_{rh} DHR(t)$
- $dDQR(t)/dt = r_d (1 - p_{dth}) p_d (1 - p_h) I(t) - r_{ri} DQR(t)$
- $dAD(t)/dt = r_d p_{dth} (1 - p_d) I(t) - r_{dth} AD(t)$
- $dDHD(t)/dt = r_d p_{dth} p_d p_h I(t) - r_{dth} DHD(t)$
- $dDQD(t)/dt = r_d p_{dth} p_d (1 - p_h) I(t) - r_{dth} DQD(t)$
- $dr(t)/dt = r_{ri} (AR(t) + DQR(t)) + r_{rh} DHR(t)$

$$dD(t)/dt = r_{dth} (AD(t) + DQD(t) + DHD(t))$$

Helper States

$$\begin{aligned} dTH(t)/dt &= r_d p_d p_h I(t) \\ dDVR(t)/dt &= r_d (1 - p_{dth}) p_d p_h p_v I(t) - r_{rv} DVR(t) \\ dDVD(t)/dt &= r_d p_{dth} p_d p_h p_v I(t) - r_{dth} DVD(t) \\ dDD(t)/dt &= r_{dth} (DHD(t) + DQD(t)) \\ dDT(t)/dt &= r_d p_d I(t) \end{aligned}$$

These coupled ordinary differential equations were solved/integrated from 15 Mar 2020 ($t = 0$ days), the first day with more than 100 total cases, up to 31 Aug 2020.

Initial Conditions for Modeling

$$\begin{aligned} N_D &= d(0) && \# \text{ Total no. of deaths } d \text{ on 15 Mar 2020 (from input data)} \\ N_R &= 5 N_D && \# \text{ Estimate for the total no. of recovered people on 15 Mar 2020} \\ N_I &= c(0) && \# \text{ Total no. of cases } c \text{ on 15 Mar 2020 (from input data)} \\ N_C &= N_I - N_R - N_D && \# \text{ No. of people who are infected and contagious on 15 Mar 2020} \\ S_0 &= N - N_C/p_d - N_C (k_1 + k_2)/p_d - N_R/p_d - N_D/p_d \\ E_0 &= N_C k_1/p_d \\ I_0 &= N_C k_2/p_d \\ AR_0 &= (N_C/p_d - N_C) (1 - p_{dth}) \\ DHR_0 &= N_C p_h (1 - p_{dth}) \\ DQR_0 &= N_C (1 - p_h) (1 - p_{dth}) \\ AD_0 &= (N_C/p_d - N_C) p_{dth} \\ DHD_0 &= N_C p_h p_{dth} \\ DQD_0 &= N_C (1 - p_h) p_{dth} \\ R_0 &= N_R/p_d \\ D_0 &= N_D/p_d \\ TH_0 &= N_C p_h \\ DVR_0 &= N_C p_h p_v (1 - p_{dth}) \\ DVD_0 &= N_C p_h p_v p_{dth} \\ DD_0 &= N_D \\ DT_0 &= N_I \end{aligned}$$

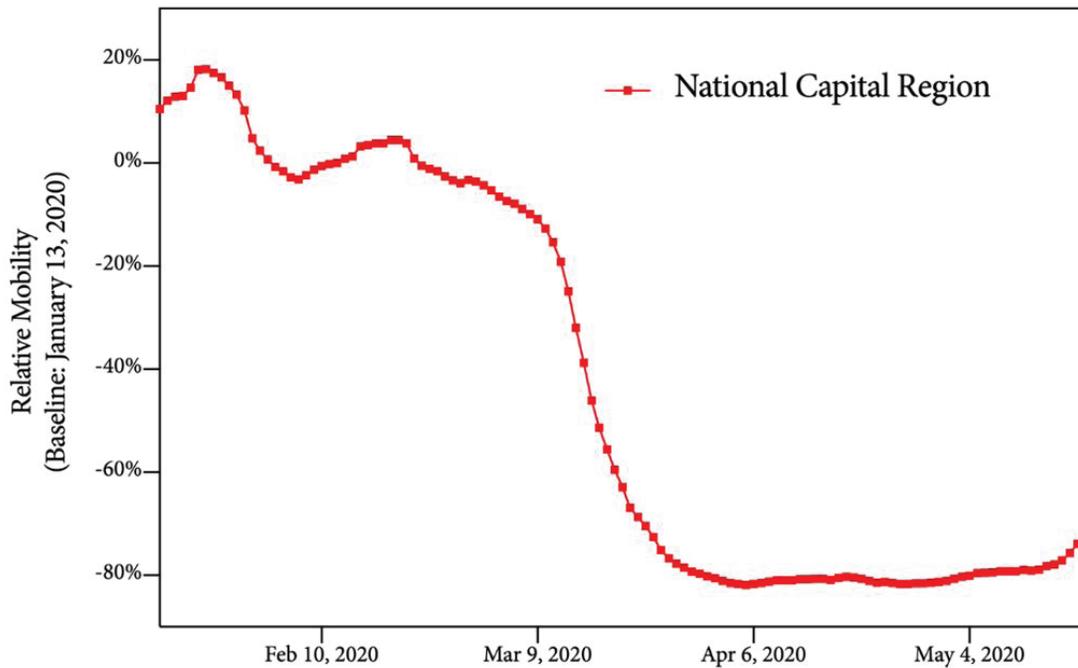
Function That Was Minimized

$$f(\alpha, t_a, L_a, r_{dth}, p_{dth}, k_1, k_2) = \text{Sum}((j + 1) (DT(j \Delta t) - c(j \Delta t))^2 + (j + 1) b^2 (DD(j \Delta t) - d(j \Delta t))^2)$$

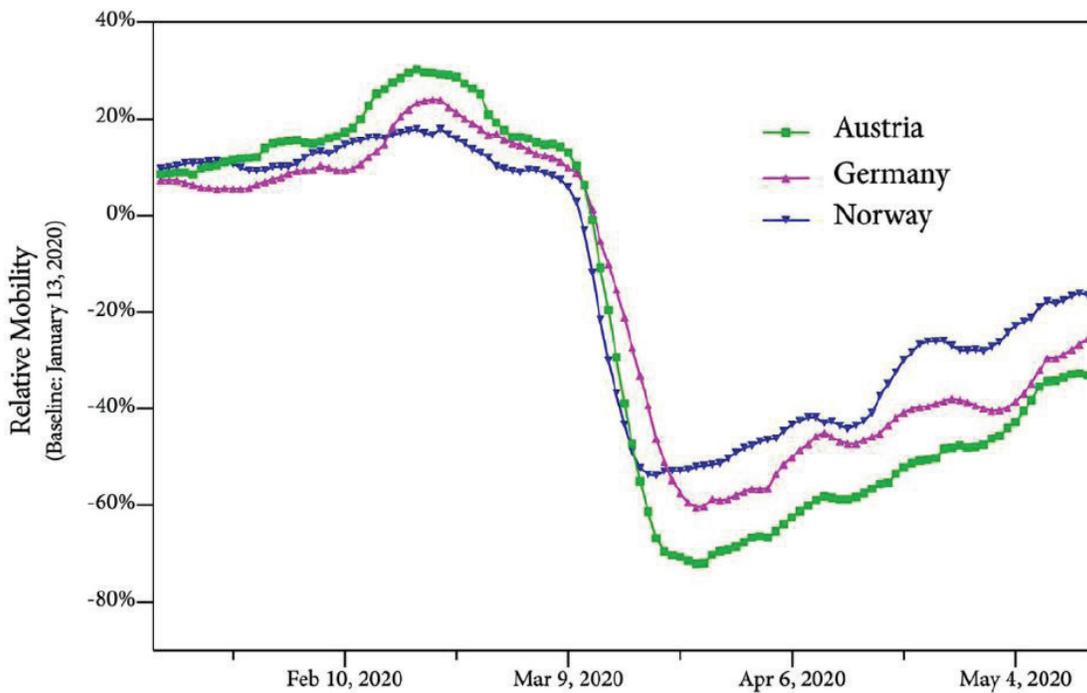
The summation is from $j = 0$ to n .

$$\begin{aligned} \Delta t &= 1 \text{ day} \\ n_D &= d(n \Delta t) && \# \text{ Total no. of deaths } d \text{ on the last day } t = n \Delta t \text{ available in the input data file} \\ n_I &= c(n \Delta t) && \# \text{ Total no. of cases } c \text{ on the last day } t = n \Delta t \text{ available in the input data file} \\ b &= n_I / (3 \max(n_D, 10)) && \# \text{ Balance: ratio of fitting between cases and deaths} \end{aligned}$$

The software accompanying this paper can be found on Github.com with the following DOI: 10.5281/zenodo.395307



Appendix Figure I. Mobility changes in NCR before and after their pandemic lockdowns. The graph was obtained by first averaging the three mobility data sets provided by Apple, Inc. – driving, walking, and transit – for each date and the calculating a seven-day running average of these means.



Appendix Figure II. Mobility changes in Austria, Germany, and Norway before and after the imposition of the ECQ. The graph was obtained by first averaging the three mobility data sets provided by Apple, Inc. – driving, walking, and transit – for each date and the calculating a seven-day running average of these means.