Efficient strategy evaluation to control the COVID-19 pandemic

Rafael Gonzalez

Universidad Mayor

Moya Pablo

University of Chile

Eduardo Bringa

University of Mendoza

Gonzalo Bacigalupe

University of Massachusetts Boston

Muriel Ramirez-Santana (✉ mramirezs@ucn.cl)

Catholic University of the North

Miguel Kiwi

University of Chile

Research Article

Keywords: COVID-19, control, Efficient strategy evaluation

Posted Date: March 17th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-305039/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Efficient strategy evaluation to control the COVID-19 pandemic

R. I. Gonzalez

*Centro de Nanotecnología Aplicada, Universidad Mayor, Santiago, Chile and
Center for the Development of Nanoscience and Nanotechnology, CEDENNA*

P. S. Moya and M. Kiwi

Departamento de Física, Facultad de Ciencias, Universidad de Chile, Santiago, Chile.

E. M. Bringa

*CONICET, Facultad de Ingeniería, Universidad de Mendoza, Mendoza, 5500 Argentina and
Centro de Nanotecnología Aplicada, Universidad Mayor, Santiago, Chile.*

G. Bacigalupe

*School of Education and Human Development, University of Massachusetts Boston, USA. and
CreaSur, Universidad de Concepción, Chile.*

M. Ramírez-Santana

*Departamento de Salud Pública, Facultad de Medicina,
Universidad Católica del Norte, Coquimbo, Chile.**

(Dated: March 13, 2021)

Many non-pharmaceutical interventions (NPI) have been implemented in several countries to prevent and mitigate the COVID-19 pandemic. In spite of the emergence of vaccines that mitigate illness and death, no effective measures exist to control the contagion. Testing, tracing, and isolation (TTI) in conjunction with disciplined social distancing were expected to achieve negligible-contagion levels and avoid, for example, superspreading events¹. However, the logic sustaining these strategies has proven insufficient and a commitment to implementing them leads to controversial ethical challenges. This paper focuses on the effectiveness of contagion control policies that are independent of the ethical challenges that the chosen strategies pose, and of the complex realities of different countries, that are applicable both country-wide and at the local level. Even more relevant is that our performance measure indicators are given by variables that provide an early warning as to when the epidemic might expand, despite some temporal case decrements. We show that if case *reduction* is not sustained for more than 7-14 days, the risk growth is considerable, warranting immediate attention and action. To draw these conclusions, our research does not only follow the contagion change but its velocity, and applies these indicators to a sample of prototypical countries, finding strong evidence for our conclusions. The latter are independent of different applied NPI and country differences, suggesting that they can be used as “universal” indicators for epidemic control policies. Our main conclusion is that if the spread reduction is lost during one, or at most two weeks, immediate measures have to be implemented to avoid undesirable scenarios.

The COVID-19 pandemic, at the time of writing this article, continues to expand worldwide despite the implementation of many non-pharmaceutical interventions (NPI)²⁻⁶. Detailed analysis of these policies utilized by different countries have been completed⁷. One of the main challenges is to estimate the threat posed by the pandemic to plan effective interventions^{8,9} that are specific and have a precise timing^{10,11}.

There are many NPIs but, in general, reducing human interactions is considered crucial¹¹. The Test, Trace, and Isolate (TTI) strategy has been shown to contribute to decreasing the epidemic growth^{5,7} when the number of new cases is low and feasible to trace. Otherwise, confinement is an alternative of control when the number of new cases is threatening to overload health services, together with an enormous social and economic impact¹². No matter which one, the NPI are measures aimed just towards reducing the number of infections and reaching

the “ideal” of zero infected cases. Available data shows that this aim alone is insufficient, since a measure that succeeds in one country might not prove to be effective in another. Quite often the data is unreliable^{13,14} due to different methodologies used to collect and process the data, among other reasons (asymptomatic cases, lack of testing, and false-negative RT-PCR tests)¹⁵⁻²⁰. But, in spite of the latter, actions are needed. For that purpose, we put forward a model focused on identifying the risk signals that the available data reveal. Ironically, we use tools developed by Isaac Newton during a long past pandemic. To do so, we consider, in addition to the number of cases and their time evolution, how the increase or decrease of cases varies in time. In other words, and in close analogy to the dynamics of motion, we incorporate in our model the speed of change of the time evolution of the number of infections.

At this point, it is essential to clarify our approach. Having zero contagion should not be taken literally;

COVID-19 will likely continue to circulate for a long time²¹. However, while there are no effective treatments or while massive vaccination is not reached, it is reasonable to seek to cut the contagion. And this can be a lesson learned for future pandemics: seek to cut or reduce the contagion while science works on safe solutions.

FIG. 1. Diagram to illustrate how the proposed performance variables are defined and calculated. The variables are the reduction rate ρ , the growth rate G , and the variation rate V .

To control the pandemic, the WHO recommends achieving “...a decline of infections of at least 50% over a 3-week period since the latest peak, and a continuous decline in the observed incidence of confirmed and probable cases...”²². Indeed, it is easier said than done and, therefore, we develop below precise data analysis to contribute quantitative criteria in line with the WHO recommendation. We start defining the seven-days reduction rate, illustrated in Fig. 1, as

$$\rho(t) = \frac{N(t) - N_{max}}{N(t)}, \quad (1)$$

where t labels a specific day, $N(t)$ is the weekly average number of cases on date t and N_{max} corresponds to a maximum of daily cases during those seven days. This way, when the number of infections decreases, $\rho < 0$.

The growth rate G instead is the ratio of the average weekly increase and the minimum of infections, that is

$$G(t) = \frac{N(t) - N_{min}}{N_{min}}, \quad (2)$$

where N_{min} corresponds to a minimum of daily cases during those seven days. Since ρ is computed relative to a maximum and G to a minimum, the former turns out to be significantly smaller numerically, a fact that has to be kept in mind when comparing their magnitudes.

The variation V is defined as follows:

$$V(t) = \frac{N(t) - N(t-7)}{N(t-7)}, \quad (3)$$

and all these time variations can be associated with a corresponding “velocity.” For example, we define the reduction velocity as

$$v_\rho(t) = \frac{d\rho(t)}{dt} \quad (4)$$

where the derivative is computed numerically with discrete differences. In the same way we define the growth and variation velocities.

Several different indicators have to be incorporated in the analysis to enhance the probability of effectively controlling COVID-19, but essentially what is required is to reduce the number of cases as fast as feasible. When a new contagion focus is found, TTI or equivalent measures may be applied, but if they do not yield prompt results (i.e., a significant reduction within 1-2 weeks), it means that the strategy is falling short. Therefore, it is useful to analyze the time variation of the variables above, i.e., the time variation of the reduction.

In order to demonstrate the usefulness of these variables, next we use them to examine three countries, with significantly different COVID-19 evolution, as prototypes: Vietnam, Australia, and the UK. We start with Vietnam, a successful crisis management example with a solid NPI that kept the total number of cases at 15 per million and the total number of deaths at 0.4 per million (February 2021). Close examination of Fig. 2a reveals that since March 2020, they have been able to keep a strong reduction rate by reacting promptly to the rise of infections. In fact, they managed to keep the reduction rate ρ , as defined in Eq. 1, in negative territory except for a slight increment in the second half of July 2020, followed by rapid reaction, but which nevertheless led to a peak of just 0.4 cases per million a day.

We now turn our attention to Australia, illustrated in Fig. 2b, which was hit by COVID-19 in early March. The reaction was swift but the weekly average number of cases reached ~ 15 per million by the end of March and was contained by the end of April. However, by mid-June ρ became positive, and the reaction was not speedy enough to prevent a second wave which peaked at 21 cases per million in mid-August and extended to early October, but has been under control since.

What happened in the United Kingdom, where the pandemic has not yet been controlled, is also worthwhile to examine critically. The reduction rate was already in positive terrain $\rho > 0$ in early March, and the number of cases per million $N(t)$ grew to ~ 100 per million by April, without a decrease until the end of June. Unfortunately, in August ρ grew again indicating that a second wave was approaching, which became quite serious by November and has not been brought under control. We write these lines (February 2021) after reaching almost 800 daily new cases per million. This confirms that the implemented strategies did not succeed.

Having perused what happened in Vietnam (a success story), Australia (initial success followed by a second wave), and the United Kingdom (where control of the

situation was lost), we can now try to infer some general behavior about epidemic management.

The data examined above suggests that, if one pays close attention to the reduction rate, two general conclusions can be drawn. The first inference is that keeping the reduction rate ρ constant is not sufficient; instead, one has to aim towards a steady decrease. Also, speedy action is required as soon as the reduction rate $\rho > 0$. Below we verify how general these prescriptions are by examination of additional available data. All of the data used below was obtained from ourworldindata.org²³.

New Zealand has been singled out as a success story in handling COVID. We now present a detailed study of what happened there, as illustrated in Fig. 3, in the light of the methodology put forward above. There was a significant outbreak in March, which prompted a vigorous reaction that reduced spectacularly, within a month, the number of cases, which then remained low for nearly two months. Thereafter, every time there was an outbreak, it was contained in a matter of days, as occurred with the August and October peaks. Each time a new outbreak, no matter how small, became manifest, there was a swift response, mainly implementing TTI, with a strong effort to trace contacts, locate the infected and put them in isolation. A similar strategy was also followed in Iceland (See Fig. S4 in S.M.). In Fig. 3a, we observe that rapid action is advisable as soon as the variation rate $V > 0$, and always keeping $\rho < 0$ for as long as possible. The dynamics are more evident when Fig. 3b is inspected, since the mid-August action and reaction are more pronounced when the velocity is plotted vs. t . These conclusions are reinforced by Fig. 3c, where we show that it is enough to follow the reduction rate and growth velocity to analyze trends.

In summary, we compute three variables and focus on their time variation: case growth, its variation, and the evolution speed. In particular, New Zealand's growth velocity is in general significantly larger than the other two variables, and allows for a rapid pinpointing of the instant case reduction beginning. Therefore, the reduction rate is central to our analysis, and furthermore allows to warn authorities and the population with a simple message: *if reduction stops, there is trouble ahead*.

We present the analysis for more than 50 other countries in the Supplementary Information. The data plotted in Fig. 4 for all those countries is intended to show that our analysis is consistent with the worldwide evolution of COVID-19. We plot the average weekly reduction rates ρ vs. the logarithm of the average number of cases in Fig. 4a and the logarithm of the average number of deaths in Fig. 4b. The countries that have fared best are located top left while the worst performers are mostly found bottom right. Again it is quite apparent that a quick response and a prolonged time negative reduction rate ($\rho < 0$) yield favorable results. Reduction alone does not predict performance well enough for some countries, like Japan, and additional indicators are

FIG. 2. Illustration of the COVID19 evolution in three countries with quite different progressions. Vietnam, a success story. Australia, which has faced a couple of serious episodes, but which lately have been overcome. The United Kingdom has not performed well, and at this time, is still facing a rather difficult moment.

FIG. 3. Time evolution of the variables. The date $t = 0$ is chosen throughout as the day the particular country exceeds 100 infections. a) Weekly averages of the number of cases, variation, reduction and growth rates as a function of time. Notice that the growth rate is many times larger than the reduction rate. b) Number of cases, their growth velocity, reduction velocity and variation velocity vs. time. c) Number of cases, their reduction and growth velocity vs. time.

FIG. 4. Data of many countries in scatter plots. a) Weekly average percentage of case reduction vs. average daily COVID-19 cases per million. Countries that have done well are consistently found upper left. b) Weekly average of the number of days COVID is reduced vs. average daily COVID-19 deaths per million; again we observe a similar country distribution as in a). c) Number of days where the reduction rate was large than 10% as vs. average daily COVID-19 deaths per million. There is a clear difference between the countries that have successfully controlled infections (upper left) and the ones that have not done so well (lower right). For each country, the daily average was calculated since they exceeded 100 accumulated cases.

It is important to point out that Fig. 4 corresponds to a snapshot taken at a precise moment and varies in time; however, the average reduction goes slowly enough to portray more than 40 countries in just one figure. These plots do not constitute a final verdict, but they allow to

spot the cases that strongly deviate from the norm. They could be related to poor tracing^{24,25}, different ways to keep statistics and/or sub-reporting.

FIG. 5. Fiji, the country with the best results among the more than 50 we analyzed. Since we computed the reduction rate when the number of total cases exceeds 100 it is not included above. Fiji has informed of only 57 cases and 2 deaths due to COVID-19 by February 25, 2021.

Finally, we must mention Fiji in Fig. 5, a country that in February 2021 has not exceeded 100 total cases, so we do not apply the variation analysis of other countries. However, it is evident that with a population close to 900 thousand inhabitants, 63 total cases per million and 2.2 total deaths per million shows it as one of the countries with the best response of all those we analyzed.

Mitigating the impact of a pandemic and achieving zero contagion is a primordial public health goal. Developing sound methodological tools to alert policy makers is essential to implement NPIs while the vaccine is still under development, fabrication, and administration. Moreover, there is uncertainty about the impact of the vaccine stopping the contagion before reaching herd immunity or preventing further reactivation of the virus or new waves of contagion.

We have presented performance indicators applicable to any NPI: reduction, growth, and variation rates (or velocities). These indicators complement other existing ones, like the effective reproduction number R_0 , and complex epidemic models^{26,27}. In fact, the application of these indicators to a large number of countries allows early warning about a likely epidemic growth, even when other indicators fail to do so. The “universality” of these indicators could signal not only the need to strengthen certain NPI in order to improve the epidemic control, but could also help with the performance evaluation of the vaccination campaigns that are already taking place in some countries.

To reach control of the epidemic, independent of the NPI implemented and of the progress in the vaccination process, significant case reduction for extended periods is necessary, keeping the growth rate under zero. The

indicators in the paper display country-wide behaviors, but they can also be applied at a more local level, and might also contribute to better management of the epidemic when only a sector of the population is considered, for instance based on age or income.

METHODS

The data for all countries was obtained from ourworldindata.org²³ on February 26, 2021, including deaths and population data. As in the first days of the epidemic the data can vary a lot, all the calculations of variations were made once the country reported more than 100 accumulated cases. Similarly, given that the data can vary significantly from day to day, we calculate the seven days moving centered case average. The rest of the variation averages are obtained as the rolling seven days average.

The reduction, growth, and variation rate were computed from the average daily cases. We define the daily rate of change of the variation, named as velocity, with finite differences. For example, the reduction velocity is computed as follows:

$$v_{\rho}(t) = \frac{d\rho(t)}{dt} \approx \frac{\rho(t-2) - 8\rho(t-1) + 8\rho(t+1) - \rho(t+2)}{\Delta 12} \quad (5)$$

where ρ is the reduction rate and t is the date. In this case we used a 4 day central finite difference.

During the first weeks of the epidemic the velocity data can be quite noisy, so we decided to calculate the velocity on the average of the reduction, growth, or variation (as appropriate) during the first three weeks after reaching 100 cases. During the rest of the days it is calculated directly on the variations without averaging. We present the averaged speed every seven days in the curves, so that they look smoother.

To calculate the total variation of Fig. 4 of the manuscript we added all the daily reductions without averaging, and they were divided by the total number of days since the 100 accumulated cases were exceeded. The reduction rate was multiplied by 100 and expressed as a positive number for clarity.

Finally, it is worth mentioning that for 7 countries we found some anomalous data that caused the calculation of the variations to be altered. This is because the countries made data corrections during the course of the emergency. As the spirit of this work is to keep it simple, we decided to replace those values with the average number of cases during the previous 7 days. For France this had to be done in many times, some were less than 7 days apart. Therefore, this procedure was followed successively in time. Some special days for France were October 25 and 26, as well as between November 2 and 4, and what we did was to replace each day with the average of those days.

All in all we tried our best to modify the data as little as possible. The total cases we used the total are the ones reported on February 26, 2021. In the Supplementary Information we include all the modified data, marked in yellow, to clarify the modifications we made.

ACKNOWLEDGMENTS

Supported by ANID Chile through Fondecyt grants Nos. 11180557, 1191351, and Center for the Development of Nanoscience and and Nanotechnology, CEDENNA AFB180001.

* mramirezs@ucn.cl

- ¹ Dyani Lewis, "Superspreading drives the covid pandemic and could help to tame it." *Nature* **590**, 544–546 (2021).
- ² Solomon Hsiang, Daniel Allen, Sébastien Annan-Phan, Kendon Bell, Ian Bolliger, Trinetta Chong, Hannah Druckenmiller, Luna Yue Huang, Andrew Hultgren, Emma Krasovich, *et al.*, "The effect of large-scale anti-contagion policies on the covid-19 pandemic," *Nature* **584**, 262–267 (2020).
- ³ Sen Pei, Sasikiran Kandula, and Jeffrey Shaman, "Differential effects of intervention timing on covid-19 spread in the united states," *Science Advances* **6** (2020).
- ⁴ Neil J. Rowan and Rafael A. Moral, "Disposable face masks and reusable face coverings as non-pharmaceutical interventions (npis) to prevent transmission of sars-cov-2 variants that cause coronavirus disease (covid-19): Role of new sustainable npi design innovations and predictive mathematical modelling," *Science of The Total Environment* **772**, 145530 (2021).
- ⁵ Adam J Kucharski, Petra Klepac, Andrew J K Conlan, Stephen M Kissler, Maria L Tang, Hannah Fry, Julia R Gog, W John Edmunds, Jon C Emery, Graham Medley, James D Munday, Timothy W Russell, Quentin J Leclerc, Charlie Diamond, Simon R Procter, Amy Gimma, Fiona Yueqian Sun, Hamish P Gibbs, Alicia Rosello, Kevin van Zandvoort, Stéphane Hué, Sophie R Meakin, Arminder K Deol, Gwen Knight, Thibaut Jombart, Anna M Foss, Nikos I Bosse, Katherine E Atkins, Billy J Quilty, Rachel Lowe, Kiesha Prem, Stefan Flasche, Carl A B Pearson, Rein M G J Houben, Emily S Nightingale, Akira Endo, Damien C Tully, Yang Liu, Julian Villabona-Arenas, Kathleen O'Reilly, Sebastian Funk, Rosalind M Eggo, Mark Jit, Eleanor M Rees, Joel Hellewell, Samuel Clifford, Christopher I Jarvis, Sam Abbott, Megan Auzenberg, Nicholas G Davies, and David Simons, "Effectiveness of isolation, testing, contact tracing, and physical distancing on reducing transmission of sars-cov-2 in different settings: a mathematical modelling study," *The Lancet Infectious Diseases* **20**, 1151–1160 (2020).
- ⁶ Nils Haug, Lukas Geyrhofer, Alessandro Londei, Elma Dervic, Amélie Desvars-Larrive, Vittorio Loreto, Beate Pinior, Stefan Thurner, and Peter Klimek, "Ranking the effectiveness of worldwide covid-19 government interventions," *Nature human behaviour* **4**, 1303–1312 (2020).
- ⁷ Amy Dighe, Lorenzo Cattarino, Gina Cuomo-Dannenburg, Janetta Skarp, Natsuko Imai, Sangeeta Bhatia, Katy AM Gaythorpe, Kylie EC Ainslie, Marc Baguelin, Samir Bhatt, *et al.*, "Response to covid-19 in south korea and implications for lifting stringent interventions," *BMC medicine* **18**, 1–12 (2020).
- ⁸ Megan O'Driscoll, Ribeiro Dos Santos, G. Wang, Lin Wang, Derek A. T. Cummings, Andrew S. Azman, Juliette

- Paireau, Arnaud Fontanet, Simon Cauchemez, and Henrik Salje, "Age-specific mortality and immunity patterns of SARS-CoV-2," *Nature* **590**, 140–145 (2021).
- ⁹ G. Pullano, Di Domenico, and C.E. et al. L., Sabbatini, "Underdetection of covid-19 cases in france threatens epidemic control." *Nature* **590**, 134–139 (2021).
- ¹⁰ Jeffery Shaman, "An estimation of undetected covid cases in france," *Nature* **590**, 38–39 (2021).
- ¹¹ Akihiro Nishi, George Dewey, Akira Endo, Sophia Neman, Sage K. Iwamoto, Michael Y. Ni, Yusuke Tsugawa, Georgios Iosifidis, Justin D. Smith, and Sean D. Young, "Network interventions for managing the covid-19 pandemic and sustaining economy," *PNAS* **117**, 30285–30294 (2020).
- ¹² Isaac Yen-Hao Chu, Prima Alam, Heidi J Larson, and Leesa Lin, "Social consequences of mass quarantine during epidemics: a systematic review with implications for the COVID-19 response," *Journal of Travel Medicine* **27** (2020).
- ¹³ Ian McCulloh, Kevin Kiernan, and Trevor Kent, "Inferring true covid19 infection rates from deaths," *Frontiers in Big Data* **3**, 37 (2020).
- ¹⁴ Peter Lloyd-Sherlock, Lucas Sempe, Martin McKee, and Aravinda Guntupalli, "Problems of Data Availability and Quality for COVID-19 and Older People in Low- and Middle-Income Countries," *The Gerontologist* **61**, 141–144 (2020).
- ¹⁵ Steven Woloshin, Neeraj Patel, and Aaron S. Kesselheim, "False negative tests for sars-cov-2 infection — challenges and implications," *New England Journal of Medicine* **383**, e38 (2020).
- ¹⁶ Rita Christiane Baron, Lorenz Risch, Myriam Weber, Sarah Thiel, Kirsten Grossmann, Nadia Wohlwend, Thomas Lung, Dorothea Hillmann, Michael Ritzler, Susanna Bigler, Konrad Egli, Francesca Ferrara, Thomas Bodmer, Mauro Imperiali, Sonja Heer, Harald Renz, Lukas Flatz, Philipp Kohler, Pietro Vernazza, Christian R. Kahlert, Matthias Paprotny, and Martin Risch, "Frequency of serological non-responders and false-negative rt-pcr results in sars-cov-2 testing: a population-based study," *Clinical Chemistry and Laboratory Medicine (CCLM)* **58**, 2131 – 2140 (2020).
- ¹⁷ Chunqin Long, Huaxiang Xu, Qinglin Shen, Xianghai Zhang, Bing Fan, Chuanhong Wang, Bingliang Zeng, Zicong Li, Xiaofen Li, and Honglu Li, "Diagnosis of the coronavirus disease (covid-19): rrt-pcr or ct?" *European Journal of Radiology* , 108961 (2020).
- ¹⁸ Lauren M Kucirka, Stephen A Lauer, Oliver Laeyendecker, Denali Boon, and Justin Lessler, "Variation in false-negative rate of reverse transcriptase polymerase chain reaction-based sars-cov-2 tests by time since exposure," *Annals of Internal Medicine* **173**, 262–267 (2020).

- ¹⁹ Michael J. Mina and Kristian G. Andersen, “Covid-19 testing: One size does not fit all,” *Science* **371**, 126–127 (2021).
- ²⁰ Daniel B. Larremore, Bryan Wilder, Evan Lester, Soraya Shehata, James M. Burke, James A. Hay, Milind Tambe, Michael J. Mina, and Roy Parker, “Test sensitivity is secondary to frequency and turnaround time for covid-19 screening,” *Science Advances* **7** (2021).
- ²¹ “Covid-19 is a marathon, not a sprint (editorial),” *Nature human behaviour* **5**, 1 (2021).
- ²² World Health Organization, *Public health criteria to adjust public health and social measures in the context of COVID-19: annex to considerations in adjusting public health and social measures in the context of COVID-19, 12 May 2020*, Technical documents (2020).
- ²³ Joe Hasell, Edouard Mathieu, Diana Beltekian, Bobbie Macdonald, Charlie Giattino, Esteban Ortiz-Ospina, Max Roser, and Hannah Ritchie, “A cross-country database of covid-19 testing,” *Scientific data* **7**, 1–7 (2020).
- ²⁴ Dyani Lewis, “Why many countries failed at covid contact-tracing-but some got it right,” *Nature* **588**, 384–387 (2020).
- ²⁵ Simon Munzert, Peter Selb, Lukas F. Stoetzer, and Will Lowe, “Tracking and promoting the usage of a covid-19 contact tracing app,” *Nature human behaviour* **5**, 247–255 (2021).
- ²⁶ Damon Centola, “Considering network interventions,” *Proceedings of the National Academy of Sciences* **117**, 32833–32835 (2020).
- ²⁷ Serina Chang, Emma Pierson, Pang Wei Koh, Jaline Gerardin, Beth Redbird, David Grusky, and Jure Leskovec, “Mobility network models of covid-19 explain inequities and inform reopening,” *Nature* **589**, 82–87 (2021).

Figures

Figure 1

Diagram to illustrate how the proposed performance variables are dened and calculated. The variables are the reduction rate p , the growth rate G , and the variation rate V .

Figure 2

Illustration of the COVID19 evolution in three countries with quite different progressions. Vietnam, a success story. Australia, which has faced a couple of serious episodes, but which lately have been overcome. The United Kingdom has not performed well, and at this time, is still facing a rather difficult moment.

Figure 3

Time evolution of the variables. The date $t = 0$ is chosen throughout as the day the particular country exceeds 100 infections. a) Weekly averages of the number of cases, variation, reduction and growth rates as a function of time. Notice that the growth rate is many times larger than the reduction rate. b) Number of cases, their growth velocity, reduction velocity and variation velocity vs. time. c) Number of cases, their reduction and growth velocity vs. time.

Figure 4

percentage of case reduction vs. average daily COVID-19 cases per million. Countries that have done well are consistently found upper left. b) Weekly average of the number of days COVID is reduced vs. average daily COVID-19 deaths per million; again we observe a similar country distribution as in a). c) Number of days where the reduction rate was large than 10% as vs. average daily COVID-19 deaths per million. There is a clear difference between the countries that have successfully controlled infections (upper left) and

the ones that have not done so well (lower right). For each country, the daily average was calculated since they exceeded 100 accumulated cases.

Figure 5

Fiji, the country with the best results among the more than 50 we analyzed. Since we computed the reduction rate when the number of total cases exceeds 100 it is not included above. Fiji has informed of only 57 cases and 2 deaths due to COVID-19 by February 25, 2021.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SuppEfficientstrategyevaluationtocontrol.pdf](#)