Lockdowns & Rebounds: A Data Analysis of What Happens Next

BARRY SMYTH, Insight Centre for Data Analytics, School of Computer Science,
University College Dublin, Ireland

We present an analysis of COVID-19 lockdowns for 56 countries based on daily mobility levels and estimated virus transmission rates. What will happen to transmission rates when countries begin to ease restrictions and mobility levels start to increase? Our analysis, based on data up to May 11th, 2020, show how, even when mobility levels increase, most countries (87%) continue to reduce the effective reproduction number (R_t) of the virus. Moreover, when restrictions were eased only after R_t was below 1, then countries always managed to maintain $R_t \leq 1$ even as mobility levels rose, at least for the period covered by the data. In contrast, when restrictions were eased before R_t fell below 1, then only 55% of countries managed to subsequently reduce R_t to below 1. By easing restrictions cautiously and carefully, it was possible to avoid a rebound in transmission rates while allowing mobility levels to increase.

CCS Concepts: • **Applied computing** → *Health informatics*;

Additional Key Words and Phrases: Data science, COVID-19

ACM Reference format:

Barry Smyth. 2020. Lockdowns & Rebounds: A Data Analysis of What Happens Next. *Digit. Gov.: Res. Pract.* 1, 4, Article 27 (August 2020), 7 pages.

<https://doi.org/10.1145/3411762>

1 INTRODUCTION

As the world struggles to respond to the speed and severity of the coronavirus pandemic [10, 15, 17, 19, 20] most countries have implemented various policies for restricting movement and commerce in an effort to control virus transmission [3, 12, 13, 18]. While approaches often begin with social distancing recommendations and a preference for *working from home*, most governments have followed up with more stringent lockdown measures, often closing non-essential services and sometimes instructing citizens to shelter-in-place while avoiding unnecessary travel. Some of the most extreme lockdowns have been implemented in Spain and Italy [14], with tens of millions of people ordered to stay in their homes for almost two months. In contrast, Sweden has chosen an alternative approach, avoiding a full lockdown in favour of strict social distancing measures while maintaining a working economy [4]. So far, the Swedish healthcare system appears to be coping—it is bending but not yet breaking—but the death rate from the virus is among Europe’s highest, and only time will tell whether this approach has been sagacious or foolish.

Supported by Science Foundation Ireland through the Insight Centre for Data Analytics under grant 12/RC/2289P2.

Authors’ addresses: B. Smyth, Insight Centre for Data Analytics, School of Computer Science, University College Dublin, Belfield, Dublin 4, Ireland; email: barry.smyth@ucd.ie.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2020 Association for Computing Machinery.

2639-0175/2020/08-ART27 \$15.00

<https://doi.org/10.1145/3411762>

With so much variety in lockdown timing, duration, and severity, it can be difficult to compare the approaches taken or their effect on transmission rates [8]. Hence, the objective of this work is to provide an objective analysis of the different lockdowns implemented by 56 different countries and how they have impacted the *effective reproduction* rate of the virus, R_t . In addition, we analyse the effect on R_t when mobility levels begin to rebound by focusing on a subset of countries that are currently easing restrictions.

2 MATERIALS & METHODS

We propose a lockdown model based on average mobility levels [4] and the effective reproduction rate of the virus [2, 6, 10] during the lockdown period. To do this, we use two separate datasets—mobility estimates and COVID-19 case numbers—covering the period of 2020 up to and including May 11.

For mobility data, we used Apple’s Mobility Trend Reports,¹ which provides daily estimates of driving, walking, and public transport use, based on requests made to Apple Maps in various countries and regions. Each daily estimate is converted into a relative change in mobility with reference to a baseline mobility period (February 17 to March 1, 2020) and the resulting relative driving, walking, and public transport data are averaged to produce a single daily, relative mobility level. Thus, a mobility level of 0.8 indicates that mobility levels have fallen by 20% from their pre-lockdown baseline. At the time of writing, comparisons between the Apple dataset and a similar dataset from Google² yield similar relative changes in mobility.

In epidemiology, R_0 , often pronounced “*r nought*,” is the so-called *basic reproduction number* and it measures the transmission potential of a virus. It is the average number of secondary infections produced by a typical case of an infection in a population where everyone is susceptible. For example, seasonal influenza has an R_0 between 0.9 and 2.1, while the measles virus has an R_0 of approximately 18; thus, in a susceptible population a typical flu sufferer can be expected to infect 1 or 2 others while someone with measles will go on to infect 18 other people. The basic reproduction number for the coronavirus (SARS-COV2) that causes COVID-19 is currently estimated to be in the range 2–5.

The effective reproduction number/rate R_t refers to the average transmission rate in a population that is made up of both susceptible and non-susceptible hosts, and where various mitigation strategies may have been implemented (e.g., face coverings, social distancing), thereby lowering the probability of transmission. Containing and ultimately eliminating a virus such as the coronavirus means reducing R_t below the critical threshold of 1.

Calculating R_t is non-trivial, but a number of approaches have been suggested, such as the one used in this work by Reference [2]. It uses statistical modelling techniques to predict the most probable value for R_t based on a time-series of confirmed case data; we use case data from the Johns Hopkins COVID-19 Data Repository [7] and the R_t estimation code is available online.³ The basic idea behind the R_t calculation is that the relationship between the number of cases yesterday and the number of cases today tells us something about the current transmission rate of the virus, and each new day of information tells the algorithm more about what R_t might be. Since the R_t estimates are derived from observed case data, they are subject to the particulars of testing in a given country, but because the algorithm uses Bayesian statistics based on the relative differences between daily cases, it is less sensitive to the vagaries of local testing policies. The end result is that it is possible to generate a daily R_t estimate for a given country, which typically falls between 0 and 4.

For the present study, we selected a subset of 56 countries for which case data (and therefore R_t estimates) and mobility data were available; not every country is included in the Apple Mobility dataset.

¹<https://www.apple.com/covid19/mobility>.

²<https://www.google.com/covid19/mobility/>.

³<https://github.com/k-sys/covid-19>.

Fig. 1. The lockdown model for Germany. The chart highlights the *Drop*, *Hold*, and *Rebound* phases of Germany's lockdown in terms of their mobility changes (M) and the corresponding estimated effective reproduction rate of the virus (R_t) for each day after the day of the 100th confirmed COVID-19 case.

3 A COVID-19 LOCKDOWN MODEL

The proposed lockdown model assumes that mobility levels (M) will transition through three distinct phases as a lockdown proceeds. The first phase, the *Drop* (D), begins when mobility levels have fallen below 90% of baseline (pre-lockdown) levels. It corresponds to the early phase of a lockdown, when restrictions are beginning to be imposed. The *Drop* can be short-lived and steep, if severe restrictions are quickly imposed, or it can be more gradual, if restrictions are introduced more slowly, allowing people some time to adapt.

Eventually, falling mobility levels will reach a minimum and the *Drop* ends on the day that levels reach within 10% of this minimum (the *hold threshold*), which marks the start of the second and most important phase of the lockdown, the *Hold* (H). The aim of the *Hold* is to sustain near-minimum mobility levels for an extended period of time to reduce the effective reproduction number of the virus by starving it of transmission opportunities.

The *Hold* finishes when mobility levels rise again and remain above the hold threshold, indicating the beginning of the final *Rebound* (R) phase. This phase sometimes coincides with a coordinated easing of restrictions, but it can also precede a formal lifting of restrictions if citizens become restless and start to move about more. If countries need to implement a sequence of lockdowns over an extended period of time, then each will have its own *Drop*, *Hold*, and *Rebound* phases, depending on the approach taken.

Figure 1 shows the model for Germany with its *Drop*, *Hold*, and *Rebound* phases indicated and colour-coded; Germany was selected as a representative example of a country, as it had passed through all of the main lockdown phases for the period of time covered by this study. The model's R_t values are also shown and colour-coded as red ($R_t > 2$), yellow ($2 \geq R_t \geq 1$), blue ($R_t < 1$); these are rolling seven-day averages of the individual daily R_t estimates. Mobility and R_t graphs are plotted against an x-axis based on the number of days since the country confirmed its 100th case; this makes it easier to compare the start of lockdowns relative to outbreak maturity, even when they begin at different times. In the supplementary appendix for this article, corresponding charts for all of the countries used in this study are available.

4 AN ANALYSIS OF LOCKDOWNS

Using this model, we can identify several important mobility and R_t features for the purpose of comparing lockdowns. We divide our countries into two groups for the period of this study—(1) those that have entered

Table 1. A Comparison of the Lockdowns for Countries That Remain in Their Hold Phase (Holders) and Those Where Restrictions Have Begun to Ease, Such That Mobility Levels Have Been Rising for > 7 Days (Rebouncers)

	Holders (n=9)		Rebouncers (n=38)		
	Drop	Hold	Drop	Hold	Rebound
Start Day	0.33 ± 9.19	15.67 ± 11.85	-3.45 ± 7.29	9.13 ± 6.08	37.53 ± 8.70
Duration	15.33 ± 4.09	43.44 ± 6.04	12.58 ± 4.02	29.39 ± 6.93	20.87 ± 8.14
Depth	0.37 ± 0.08	0.72 ± 0.12	0.33 ± 0.06	0.66 ± 0.12	0.54 ± 0.13
Degree	5.69 ± 1.80	31.33 ± 7.55	4.18 ± 1.50	19.25 ± 5.82	10.98 ± 4.37
R_t	2.02 ± 0.25	1.09 ± 0.23	2.15 ± 0.51	1.04 ± 0.23	0.89 ± 0.27

their *Rebound* phase (*Rebouncers*) with rising mobility levels for more than seven days and (2) those that remain in their *Hold* phase (*Holders*). Table 1 presents the mean and standard deviation values for these cohorts in terms of the following key lockdown features:

- (1) *Start Day*: the start of the phase (*measured in days*) relative to the day when the 100th confirmed case was recorded.
- (2) *Duration*: the *length of the phase* (*Drop*, *Hold*, or *Rebound*), also measured in days.
- (3) *Depth*: the *average percentage drop* in mobility levels (relative to pre-lockdown levels) for the phase.
- (4) *Degree*: an estimate of the *severity of the lockdown*, calculated as the duration of the phase multiplied by the degree of the phase; effectively the cumulative mobility drop for the duration of the lockdown phase.
- (5) R_t : the effective reproduction number estimate (seven-day rolling average) on the last day of each phase.

In Table 1, we can see how, on average, *Rebouncers* started their lockdowns approximately four days before *Holders*—3.45 days *before* the 100th case vs. 0.33 days *after* their 100th case, respectively—but this difference is not statistically significant based on a one-sided t test ($P = 0.095$, $t_{45} = -1.33$).

The duration (days), depth (average drop in mobility), and degree ($\text{duration} \times \text{depth}$) of the *Drop* and *Hold* phases for *Rebouncers* is less than it is for *Holders*. For example, the degree of the *Drop* is significantly lower for *Rebouncers* than for *Holders*, based on a one-sided t test ($P = 0.0033$, $t_{45} = -2.6337$) and likewise for the degree of the *Hold* ($P = 0.000$, $t_{54} = -5.2888$). In other words, rebounding countries that have been easing restrictions are associated with less severe lockdowns—lower *Hold* degree—than those counties still in their *Hold* phase. Despite their less severe *Holds*, however, *Rebouncers* exited their *Hold* phase with a similar R_t as *Holders* currently have (as of May 11th, 2020): 1.04 vs. 1.09, respectively (see Table 1), a marginal difference that is not statistically significant based on a one-sided t test ($P = 0.3134$, $t_{45} = -0.4897$).

What will happen to R_t after restrictions are eased for the current *Holders*? Will transmission rates increase, resulting in a second surge of infections, or can we expect R_t to remain below the critical threshold of 1, even as mobility levels increase? Figure 2 shows the differences between the R_t estimates at the end of the *Hold* and the current *Rebound* phases for the 38 countries currently in *Rebound*, sorted in descending order of the number of days since their *Rebound* phases began.

The data in Figure 2 indicate that 87% of *Rebouncers* have been able to continue to reduce R_t even as mobility levels have been rising. The mean R_t for *Rebouncers* is currently 0.89, compared with 1.04 when they exited their *Hold* phase (Table 1), a difference that is statistically significant based on a one-sided t test ($P = 0.0047$, $t_{74} = -2.6678$).

If we distinguish between *risky* and *cautious Rebouncers*, based on whether they exited their hold phase with $R_t > 1$ (risky) or $R_t \leq 1$ (cautious), then we observe that, as of May 11th, 2020, all 18 of the cautious *Rebouncers*

Fig. 2. A comparison of R_t estimates at the end of the *Hold* and *Rebound* phases for *Rebounders* (bar graph). Countries are arranged in descending order of the duration of their rebound phase, which is also indicated as the line graph.

still have $R_t \leq 1$, in comparison to just 11 (55%) of the risky *Rebounders*; the mean R_t for cautious *Rebounders* is currently just 0.70, compared with 1.06 for risky *Rebounders*, a difference that is statistically significant based on a one-tailed t test ($P = 0.00$, $t_{36} = 5.5733$).

Moreover, the longer the *Rebound* phase, the more likely countries are to reduce or maintain R_t below 1. For example, in Figure 2, we can see that all but one of the countries that have been in *Rebound* for more than three weeks have $R_t < 1$, regardless of whether they entered the *Rebound* phase with $R_t < 1$ or not, suggesting that given time, even risky *Rebounders* can reduce R_t below 1, if the easing of restrictions is managed correctly and carefully.

5 CONCLUSIONS

These results bode well for countries as they plan and implement their lockdown exit strategies. So far, the data for 38 rebounding countries do not show an increase in transmission rates even as mobility levels have increased. Instead, the data suggest that by carefully exiting the *Hold* phase, countries can continue to lower R_t even as mobility levels increase. And by avoiding the temptation to rebound before $R_t \leq 1$, countries can significantly improve the likelihood that they will preserve their $R_t \leq 1$ status during their *Rebound*. However, it remains to be seen how long this can be sustained. This study corresponds to a specific point in time during the 2020 coronavirus outbreak. The snapshot of data includes some countries that have been in *Rebound* for up to five weeks, but only time will tell whether transmission rates will stay low for longer periods.

All of this suggests that the restrictions imposed during lockdowns serve two important purposes. On the one hand, they eliminate many of the usual opportunities for virus transmission; on the other hand, lockdowns also create the time and space, and the impetus, for people to assimilate a new set of behaviours and norms [1]—better social distancing [13], improved hand-hygiene [5], the proper use of facemasks [9], and so on—that are compatible with the need to co-exist with the coronavirus in our communities [11, 16]. Perhaps the very nature of the lockdown, and the desire it creates in us all to return to some degree of normalcy, is in itself an effective social treatment to protect us, by reducing risky behaviours as restrictions are eased, at least for now. That being said, we must remember that, even though mobility levels are rising in the period covered by this study, they still

remain below pre-lockdown levels. It seems unlikely that this protection, such as it is, will remain indefinitely, especially if mobility levels continue to rise or if we become too complacent.

REFERENCES

- [1] Jay J. Van Bavel, Katherine Baicker, Paulo S. Boggio, Valerio Capraro, Aleksandra Cichocka, Mina Cikara, Molly J. Crockett, Alia J. Crum, Karen M. Douglas, James N. Druckman, John Drury, Oeindrila Dube, Naomi Ellemers, Eli J. Finkel, James H. Fowler, Michele Gelfand, Shihui Han, S. Alexander Haslam, Jolanda Jetten, Shinobu Kitayama, Dean Mobbs, Lucy E. Napper, Dominic J. Packer, Gordon Pennycook, Ellen Peters, Richard E. Petty, David G. Rand, Stephen D. Reicher, Simone Schnall, Azim Shariff, Linda J. Skitka, Sandra Susan Smith, Cass R. Sunstein, Nassim Tabri, Joshua A. Tucker, Sander van der Linden, Paul van Lange, Kim A. Weeden, Michael J. A. Wohl, Jamil Zaki, Sean R. Zion, and Robb Willer. 2020. Using social and behavioural science to support COVID-19 pandemic response. *Nature Hum. Behav.* 4, 5 (May 2020), 460–471.
- [2] Luis M. A. Bettencourt and Ruy M. Ribeiro. 2008. Real time Bayesian estimation of the epidemic potential of emerging infectious diseases. *PLoS One* 3, 5 (May 2008), e2185.
- [3] Benjamin J. Cowling, Sheikh Taslim Ali, Tiffany W. Y. Ng, Tim K. Tsang, Julian C. M. Li, Min Whui Fong, Qiuyan Liao, Mike Yw Kwan, So Lun Lee, Susan S. Chiu, Joseph T. Wu, Peng Wu, and Gabriel M. Leung. 2020. Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in Hong Kong: An observational study. *Lancet. Pub. Health* 5, 5 (May 2020), e279–e288.
- [4] Matz Dahlberg, Per-Anders Edin, Erik Grönqvist, Johan Lyhagen, John Östh, Alexey Siretskiy, and Marina Toger. 2020. Effects of the COVID-19 pandemic on population mobility under mild policies: Causal evidence from Sweden. *arXiv preprint arXiv:2004.09087* (2020).
- [5] Rachel Dickie, Susan Rasmussen, Rachel Cain, Lynn Williams, and William MacKay. 2018. The effects of perceived social norms on handwashing behaviour in students. *Psychol. Health Med.* 23, 2 (Feb. 2018), 154–159.
- [6] O. Diekmann, J. A. Heesterbeek, and J. A. Metz. 1990. On the definition and the computation of the basic reproduction ratio R_0 in models for infectious diseases in heterogeneous populations. *J. Math. Biology* 28, 4 (1990), 365–382.
- [7] Ensheng Dong, Hongru Du, and Lauren Gardner. 2020. An interactive web-based dashboard to track COVID-19 in real time. *Lancet. Infect. Dis.* 20, 5 (May 2020), 533–534.
- [8] Thomas Hale, Anna Petherick, Toby Phillips, and Samuel Webster. 2020. Variation in government responses to COVID-19. *Blavatnik School Gov. Work. Paper* 31 (2020).
- [9] Nancy H. L. Leung, Daniel K. W. Chu, Eunice Y. C. Shiu, Kwok-Hung Chan, James J. McDevitt, Benien J. P. Hau, Hui-Ling Yen, Yuguo Li, Dennis K. M. Ip, J. S. Malik Peiris, Wing-Hong Seto, Gabriel M. Leung, Donald K. Milton, and Benjamin J. Cowling. 2020. Respiratory virus shedding in exhaled breath and efficacy of face masks. *Nat. Med.* 26, 5 (May 2020), 676–680.
- [10] Ying Liu, Albert A. Gayle, Annelies Wilder-Smith, and Joacim Rocklöv. 2020. The reproductive number of COVID-19 is higher compared to SARS coronavirus. *J. Trav. Med.* 27, 2 (Mar. 2020).
- [11] Peter D. Lunn, Cameron A. Belton, Ciarán Lavin, Féidhlim P. McGowan, Shane Timmons, and Deirdre A. Robertson. 2020. Using behavioral science to help fight the coronavirus. *J. Behav. Pub. Admin.* 3, 1 (2020).
- [12] Calistus N. Ngonghala, Enahoro Iboi, Steffen Eikenberry, Matthew Scotch, Chandini Raina MacIntyre, Matthew H. Bonds, and Abba B. Gumel. 2020. Mathematical assessment of the impact of non-pharmaceutical interventions on curtailing the 2019 novel coronavirus. *Math. Biosci.* 325 (2020), 108364.
- [13] Kiesha Prem, Yang Liu, Timothy W. Russell, Adam J. Kucharski, Rosalind M. Eggo, Nicholas Davies, Mark Jit, and Petra Klepac. 2020. The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: A modelling study. *Lancet. Pub. Health* 5, 5 (May 2020), e261–e270.
- [14] Aurelio Tobias. 2020. Evaluation of the lockdowns for the SARS-CoV-2 epidemic in Italy and Spain after one month follow up. *Sci. Total Environ.* 725 (July 2020), 138539.
- [15] Robert Verity, Lucy C. Okell, Ilaria Dorigatti, Peter Winskill, Charles Whittaker, Natsuko Imai, Gina Cuomo-Dannenburg, Hayley Thompson, Patrick G. T. Walker, Han Fu, Amy Dighe, Jamie T. Griffin, Marc Baguelin, Sangeeta Bhatia, Adhiratha Boonyasiri, Anne Cori, Zulma Cucunubá, Rich FitzJohn, Katy Gaythorpe, Will Green, Arran Hamlet, Wes Hinsley, Daniel Laydon, Gemma Nedjati-Gilani, Steven Riley, Sabine van Elsland, Erik Volz, Haowei Wang, Yuanrong Wang, Xiaoyue Xi, Christl A. Donnelly, Azra C. Ghani, and Neil M. Ferguson. 2020. Estimates of the severity of coronavirus disease 2019: A model-based analysis. *Lancet. Infect. Dis.* 20, 6 (June 2020), 669–677.
- [16] Robert West, Susan Michie, G. James Rubin, and Richard Amlôt. 2020. Applying principles of behaviour change to reduce SARS-CoV-2 transmission. *Nat. Hum. Behav.* 4, 5 (May 2020), 451–459.
- [17] Jing Yuan, Minghui Li, Gang Lv, and Z. Kevin Lu. 2020. Monitoring transmissibility and mortality of COVID-19 in Europe. *Int. J. Infect. Dis.* 20 (2020), 1878:3511.
- [18] Juanjuan Zhang, Maria Litvinova, Yuxia Liang, Yan Wang, Wei Wang, Shanlu Zhao, Qianhui Wu, Stefano Merler, Cécile Viboud, Alessandro Vespignani, Marco Ajelli, and Hongjie Yu. 2020. Changes in contact patterns shape the dynamics of the COVID-19 outbreak in China. *Science* 368, 6498 (June 2020), 1481–1486.

- [19] Sheng Zhang, Meng Yuan Diao, Liwei Duan, Zhaofen Lin, and Dechang Chen. 2020. The novel coronavirus (SARS-CoV-2) infections in China: Prevention, control and challenges. *Intens. Care Med.* 46, 4 (Apr. 2020), 591–593.
- [20] Shi Zhao, Zian Zhuang, Peihua Cao, Jinjun Ran, Daozhou Gao, Yijun Lou, Lin Yang, Yongli Cai, Weiming Wang, Daihai He, and Maggie H. Wang. 2020. Quantifying the association between domestic travel and the exportation of novel coronavirus (2019-nCoV) cases from Wuhan, China, in 2020: A correlational analysis. *J. Trav. Med.* 27, 2 (Mar. 2020).

Received June 2020; revised July 2020; accepted July 2020