# <u>**Lockdowns and Closures vs COVID – 19: COVID Wins**</u>

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**Abstract:**

Using cross-country COVID and broad economic data for over 160 countries, we estimate most of the models presented in the literature on the impact of non-pharmaceutical interventions (NPI) on the diffusion of COVID across the world. A very large majority of the papers conclude that the aggregate form of NPI's – lockdowns - were successful in reducing infections, or deaths, or both. When not successful, the literature argues that failure was due to bad implementation i.e. the lockdown was implemented later than optimal, or accompanied by too little stringency. In addition to those present in the literature, we add the following important test of lockdowns – a before and after comparison for 143 countries, and for one, two, and three months from the date of lockdown. No matter what the test, the dominant result is that not only lockdowns were not effective, but that, in a large majority of cases, lockdowns were counter-productive i.e. led to more infections, and deaths than would have been the case with no lockdowns.

The paper also attempts to rank countries in terms of performance i.e. evaluation of what happened versus what should have happened post interventions. Three months after lockdowns, in only 18 countries lockdowns led to "good performance"; with stricter definition of success, the number falls to only 8 countries.

We also test, in some detail, the hypothesis that early lockdowns, and more stringent lockdowns, were effective in containing the virus. We find robust results for the opposite conclusion: later lockdowns performed better, and less stringent lockdowns achieved better outcomes,

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## Introduction

Three hundred days plus and counting Covid. The year 2020 has been a long journey into the unknown, a journey that the entire world has taken together. This is also the age of technology and communication – hence, the spread of information and analysis has been instantaneous, and something never witnessed before. Unlikely that there is a single village (perhaps single household) that has not heard of COVID19. Unlikely, because every country has witnessed Covid cases, and most governments responded with alacrity by instituting lockdown measures to combat the virus.

The concern in this paper is with this very important aspect of the pandemic i.e. how effective were lockdowns (also referred to as non-pharmaceutical interventions (NPI)) in arresting the spread of the virus? Effectiveness evaluated in terms of infections reduced, or deaths reduced, or both. The NPIs were meant to flatten the curve – and the question examined is the degree to which flattening was achieved by NPIs. Nowadays "curve flattening" is a household term, and with many meanings, but the dominant interpretation is that flattening means an extension of the *duration* of the epidemic without compromising on the ceiling (terminal) level of infections (or deaths)[1]. Flattening is meant to decrease the peak load to levels the health system can manage (no overload on hospital beds, ventilators etc.).

It is an unfortunate fact that the pandemic came very suddenly for most countries, the suddenness being akin to an earthquake. For most countries (if not all, excluding China) there was little time for governments to respond. By end-March panic had set in with infections in the world more than 140 times higher, and deaths 440 times higher, than that observed near the end of the pandemic in China, end-February. Especially meaningful for the world community were the numbers and visuals from Italy – from less than 30 deaths per day end-February to more than 800 deaths/day end March.

[1] The analysis for Covid cases and deaths is done in parallel; hence, reference to cases implies that a corresponding analysis of deaths has also been undertaken; the concentration in this paper is dominantly on infections.

On the advice of experts (epidemiologists, health experts) governments around the world chose a unique way to wage war against the virus – the chosen weapon was a lockdown of economy and society. Simply stated, citizens were asked to stay indoors, in their homes, so that they would not be in contact with anyone who had the virus. If they stayed home long enough the virus would, in theory and hopefully in practice, would die on its own. This lockdown took several forms, and there is no record of such lockdowns ever occurring on an international scale before[2].

The effect on economies was immediate and completely expected – when you close the economy (or people), output produced would be less. But what about the effect on virus diffusion and containment? The world, correctly, turned to expert epidemiologists to show the light. Early on, what the world heard was frightening. Experts at Imperial College, London, projected this scenario. "In total, in an unmitigated epidemic, we would predict approximately 510,000 deaths in GB and 2.2 million in the US, not accounting for the potential negative effects of health systems being overwhelmed on mortality." (Ferguson et. al., p. 7)

Given the popularity of pandemic containment policies, it is important that a proper understanding be in place for future pandemics, as well as possibly a second (or third) wave of COVID.[3] The research community (economists, demographers, epidemiologists and data scientists) has undertaken numerous studies and published results in all forums. The objective of several of these studies has been the same – did NPI's flatten the curve, and if so, to what extent.

The plan of the paper is as follows. Section 2 studies the origins of the crisis, and the origins of state response. The section ends with a discussion of the 1957-58 flu (H1N2) epidemic, an event with close parallels to COVID19. Section 3 describes the various sources of data. The international community, led by Johns Hopkins university, has led the way with making all data pertaining to Covid free of charge. Evidence is presented on both the universality of the crisis, and the near perfect simultaneity of worldwide deployment of lockdowns, closures etc. to stem

[2] The 2018 SARS virus did involve localized lockdowns in China and Hong Kong.

[3] The world is now experiencing a second wave, but what proportion of the second wave is a direct consequence of higher asymptomatic cases (due to increased testing), and how much due to increased pre-testing type infections is an open question, and a preliminary discussion of the issues involved is presented in Section 7. It is an open question whether the recent second wave of infections is being caused by problems created, or not solved, by lockdowns.

the crisis. Not even a tenth of such extreme measures were ever tried before. Section 4 outlines what it means to flatten the curve and discusses the various empirical formulations used by experts to identify the "correct" representation of non-linear diffusion processes. It turns out that the Gompertz curve is the weapon of choice for analysis – and that estimating the effect of *individual* lockdown policies like school closures, border closures etc. is econometrically inappropriate; this because individual policies were implemented *jointly* with other policies. Section 5 corrects for the specification error and uses the Gompertz curve formulation to test for the effect of lockdowns on infections and deaths in a multi-country framework. Using all available methods of analysis, we conduct over 2000 tests (different definitions of NPIs and different regions of the world) and find that in less than 15 % of country-time aggregations was a lockdown pro-active in reducing the growth rate of infections. More worryingly, lockdowns had a significant *perverse* effect in over 80 % of the countries i.e. steepened the curve and increased the total infections to a level well beyond no interventions. The result – less policies were more effective, *ceteris paribus*.

Section 6 offers a "new" rigorous test for interventions; it develops and estimates a before-after model of interventions for *each* of 143 countries. Performance indices were estimated for each country, and from individual country estimates, performance indices for different regions of the world. The period of analysis (for this exercise) ends around late July early August; extending the estimation post these dates would bias the results against the effectiveness of interventions. Three months after lockdown, which generally occurred in March, only 18 countries achieve performance close to the counter-factual no-lockdown forecasts. This robust estimation (via individual Gompertz curves for each country) ends up with the same surprising result – lockdowns, or variations thereof, were **not** successful in reducing infections (or deaths) across the world. The pandemic has induced many false positives (and false negatives). The only safe conclusion likely is that one must estimate many models of diffusion, and interventions, before arriving at any reliable conclusions.

Section 7 tests for the broad effect of increased testing on increased infections (very high) and for the controversial hypothesis that if lockdowns had been quicker, and more stringent, COVID-19 cases would not be so many. Little support for this conclusion is obtained. Section 7 also offers a preliminary analysis of the new alternative to lockdown strategy (3-T: Test, Trace, and Treat) being practiced in India post July 31. Section 8 concludes with some reflections, and conclusions.

## Section 2 – Background to the Crisis

*The Wuhan Experience*

A brief timeline of COVID cases in the city of origin, Wuhan, is as follows. December 15, 2019 is dated to be the first known case, and Dec. 31, 2019, the number of known cases in Wuhan had climbed to 27.[4] On January 23rd, Wuhan was under lockdown, with the number of confirmed cases at 882 and only 26 confirmed deaths.

Lockdowns had never been implemented before, not even during the "extreme" flu epidemics of 1957-58 and 1961. The Wuhan experience has been much studied, with a mixed conclusion on its effectiveness. It is likely to be studied even more as there has been some disappointment with the economic cost lockdowns have imposed, especially for the poor. There was talk of a trade-off – a lockdown imposed economic downturn compensated with positive health outcomes due to the lockdown.

It was natural for policymakers (and politicians) to accept whatever solutions were offered by the health experts. And the experts were near unanimous in favor of lockdowns, notwithstanding the fact that a lockdown was according to all definitions a "new" (unnatural) experiment. The drastic unprecedented nature of lockdowns (while masks[5] and social distance are part of the history of virus-containment, closure and lockdowns are new entrants) was likely affected by the documentation of how China, in particular the place of origin, Wuhan, dealt with this new SARS2-Covid19 strain. As is well-known, no vaccine for the Corona strain exists, and policymakers were

[4] The JHU database documents cases (and deaths) for all countries since Jan. 22nd. The European Commission database contains data since December 31 2019.

[5] Even masks are a late entrant as an anti-containment measure. According to WHO(2019, p. 42) recommendations of what to do in a virus pandemic, symptomatic persons and persons with respiratory illnesses "should" wear masks, while exposed persons should consider it (but only based on risk assessment). No guidelines for the rest of the population.

pressured to act quick before the infection spread widely.[6] The early conclusion on Wuhan was that it was immensely successful in containing the virus in China. This conclusion was prominent in the minds of most policy-makers as they embarked on the ambitious exercise of shutting down economies.

More than nine months have passed since the first lockdown, and now might be the most appropriate time to rigorously examine the outcomes and the effectiveness of the lockdowns. A rigorous evaluation of the health efficacy of lockdowns cannot be over-emphasized. Our conclusion is that there is little convincing scientific basis that lockdowns work; the scientific community needs to dispassionately examine all the evidence on lockdowns, including ours.

*Expert Analysis and Advice*

In an influential article published in the *New England Journal of Medicine* (*NEJM*) on March 26th 2020 (and circulated on NEJM website as early as January 29, 2020)) several (numbering close to 75) China Disease Control (CDC) authors (Qun Li et. al.) concluded that

"there is evidence that human to human transmission has occurred among close contacts since the middle of December 2019. Considerable efforts to reduce transmission will be required to control outbreaks if similar dynamics apply elsewhere. Measures to prevent or reduce transmission should be implemented in populations at risk."

The paper also noted that

"our preliminary estimate…provides important evidence to support a 14-day medical observation period or quarantine for exposed persons. Our estimate was based on information from *10 cases and is somewhat imprecise*" (emphasis added).

The Li NEJM paper did not offer any concrete analysis of the efficacy of lockdowns (the lockdown in Wuhan was just a week earlier and it was too early to ascertain its success or failure). However,

[6] As of mid-October, the tragedy is that the virus has not been contained, almost anywhere in the world (except, relative to population in the country of origin China, Viet-Nam and some other south-east Asian economies). Analysis of why China was so successful via lockdowns, and other countries were not, is a subject that historians will analyze in a few years..

in a paper dated March 17, 2020, Lau et.al describe in detail the lockdown in Wuhan city. Lockdown meant travel restrictions to and from Wuhan, closure of schools, colleges, and public places, prohibition of mass gatherings, and enforcement of strict social distancing measures. Lau et. al. note that with the imposition of the lockdown on 23rd January,

"Outside activities were extremely limited since every citizen was given a permission card and only allowed to leave their home every second day for a maximum of 30 minutes. Despite this rigorous enforcement launched by China to contain COVID-19 spread, *total case numbers have significantly increased in China and internationally*." They further note that "travel restrictions have demonstrated a positive effect in past SARS, Ebola and bubonic plague outbreaks. The measures implemented in Wuhan and the entire Hubei region of China exceed by far the classic definition of local confinement, lockdown and isolation". (p. 1-2; emphasis added).

Nevertheless, Lau et. al.  conclude:

"a significantly decreased growth rate and increased doubling time of cases was observed, which is most likely due to Chinese lockdown measures."

In a paper published on April 6, Figueiredo et.al. (WHO Bulletin) concluded that "Strict social distancing measures were effective in reducing incidence and mortality rates (in Wuhan)". Citing a European Center for Disease Prevention and Disease Control study, the authors add

"More comprehensive social distancing measures, such as temporary suspension of school activities, events involving large crowds, or closing borders, are also recommended in specific situations, despite *the lack of evidence of effectiveness*" (emphasis added).

Nevertheless, Figueiredo et.al. conclude (p.7)

"that the *lockdown was effective* in reducing incidence and mortality rates in Hubei and in adjacent regions like Guangdong. *Thus, it can be used as a strategy to reduce the spread of the COVID-19 pandemic*". (emphasis added).

These conclusions, supplemented by the authoritative WHO publications, convinced policy makers around the world to adopt Wuhan-style strict containment policies as early as mid-March 2020.

*Efficacy of lockdown in China*

Yuan et.al. (2020) look at migration data, into and out of Wuhan, to provide specific estimates of the effects of lockdown.[7] According to their estimates, more than 9 million residents were isolated in Wuhan post 23rd January; and 1.2 million either entered or left Wuhan between 23rd January and February 15. The authors rank 29 provinces of China (excluding the province containing Wuhan city, Hubei) in terms of the "effectiveness of interventions to prevent transmission of COVID-19". Three provinces were ranked excellent, five were ranked good; five were ranked very poor, and two were ranked poor. A similar exercise was carried out by the authors for 44 prefecture level cities – and similar results obtained. Four prefectures were graded excellent, and nine were graded good; four were graded very poor, and five were graded poor.

On March 10, the WHO declared COVID19 to be a pandemic. On the same day, Italy entered into a lockdown, some 41 days after knowledge of the first case, and 18 days after the 27th case (in China it was 22 days after the 27th case). But on this twenty-seventh day in Italy, there were more than 10000 infections, compared to only 623 in China on their 22nd day. Guzetta et. al. (2020) document that fourteen days after the lockdown (March 24th) in Italy, the net reproduction of virus number R0 had dropped to below 1 i.e. the lockdown was a success. However, as we will document later in Section 4, the use of R0 as a measure of success/failure of containment policies is problematical, as also discussed in detail very recently by Tufekci (2020).

The logic of a containment policy is as follows – apply restrictions (early) to bring down the growth rate of infections. We will revisit this issue several times in our discussion but at this

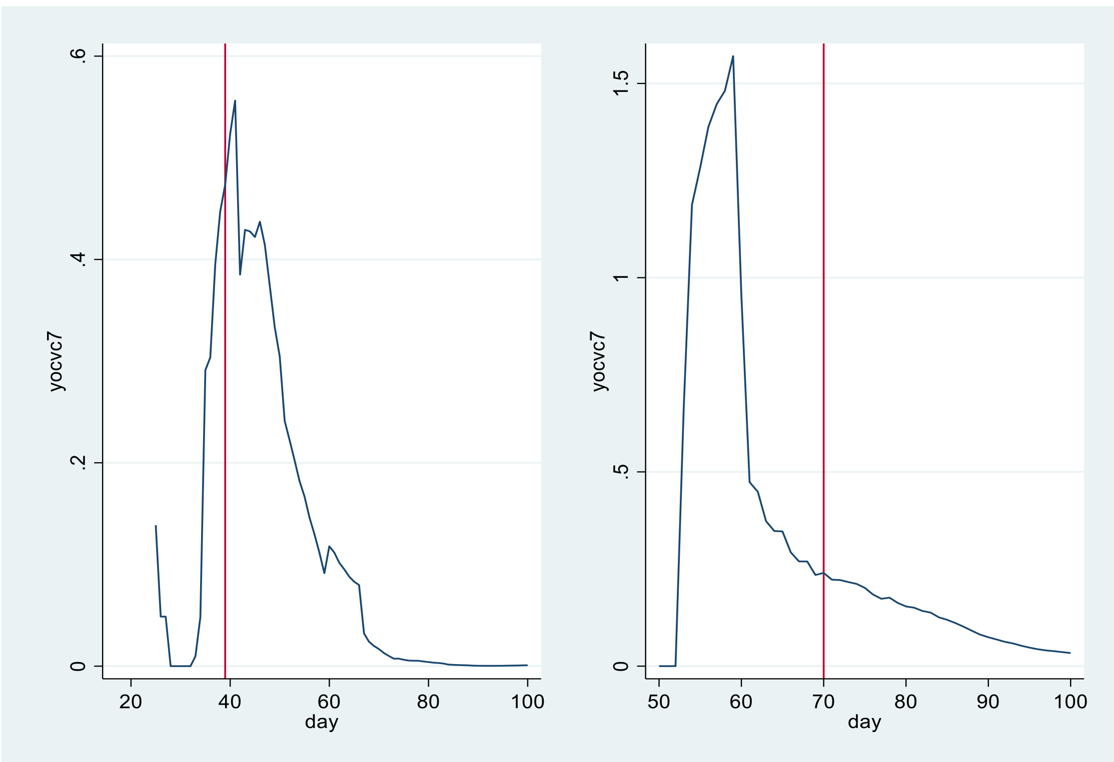
[7] See Virmani-Bhalla(2020a) and a NYT article ("How the Virus Got Out") for a correlation type analysis of the likely mechanisms of the transmission of the virus outside China.

juncture it is worth just displaying the pattern of the average seven-day growth rate in infections in the two countries that first employed lockdown policies, China and Italy.

Red lines represent day of the lockdown; Y-axis is the average 7 day growth rate of cases; X-axis is number of days since Jan 1st, 2020. The X-axis measures the days since the emergence of the virus – for China the first date is taken as December 15, 2019 and for Italy the first day of the virus was on January 30, 2020 or day 30 in calendar time. The Red line denotes the day of lockdown – January 23rd for China and March 10th for Italy.

**Figure 1: Seven-day average rate of growth in cases – before and after lockdown**

*China* *Italy*




*Source: JHU data; author computations*

What is striking about this raw data is that the Chinese lockdown happened just before the peak in growth rates, and in the case of Italy, well beyond the peak and when considerable decline in the infection growth rate had already set in. In this regard, it is relevant to note what the commentary was on the efficacy of lockdowns, and commentary that lockdowns were successful in the two countries that had tried it, China and Italy, may have led other policy makers around the world to experiment with lockdowns.

A significantly decreased growth rate of infections is the *norm* at the stage it was imposed in China. In a sample of 162 countries, an overwhelming percentage (more than 75 percent) show a decline in the seven-day average growth rate post day 37 of the virus. This decline in average growth, at this stage of the virus diffusion, is also supported by the logistic and Gompertz models of diffusion (see section 4). In other words, *a declining growth rate per se is not evidence that the Wuhan lockdown was successful.*

An expert group (Guzetta et. al) set up in Italy to study the consequences of the virus reported as follows.

"Our results suggest that the restrictive interventions put in place to limit the spread of SARS-CoV-2 in Italy have been successful in bringing the reproduction number significantly below 1 within two weeks from the national lockdown on March 11, 2020…Italy was the first country in the western hemisphere to impose a nationwide lockdown, although with softer restrictions compared to the Chinese experience. Many countries worldwide followed Italy in the same decision…. The effectiveness of lockdown interventions had been shown in China"".

In the Abstract, the authors confidently conclude

Our findings provide a timeline of the effectiveness of the implemented lockdown, which is relevant for a large number of countries that followed Italy in enforcing similar measures." (Members of the COVID-19 working group) Guzetta et.al., 2020.

In the case of China we can speculate about the worth of a lockdown, but in the Italian case it is obvious that the virus decline had well and truly settled in, and the restrictions may have had very little to do with the eventual successful demise of the virus. This conclusion is strictly based on the pattern of growth rates reported above. More detailed presentation in Section 5 supports this conclusion.

Regarding lockdown in China, the virus-containment numbers are impressive. As of September 30, only 90,000 odd infections were observed in China, in a population four times the size of the

USA. The performance is even more impressive if one looks at the number of *deaths* due to influenza in the US in 2018/19, a disease for which a vaccine was widely available, and used. Total deaths in China from COVID-19 –4739; influenza deaths in the US in 2019 – 34200. In other words, the flu death rate in US in 2019 was more than seven times the Covid death rate in China in 2020.[8] Why China was able to control the infection rate and not the death rate is a subject deserving further examination. End October 2020, the Covid fatality rate in China was 5.2 % i.e. out of every 1000 people infected by COVID in China, 52 died. This represented the 92nd percentile i.e. only 8 % of 160 countries had a higher case fatality rate than China.

**No lockdown during comparable flu epidemics of 1957-58 and 1960 – Why?**

The question remains - did the world have an option other than a lockdown? There has been constant invocation of the Spanish 1918 pandemic as an appropriate parallel for 2020; but as Niall Ferguson reminds us, possibly the flu pandemics of the late 1950s are a more appropriate "benchmark", a subject we examine next.

In the six month Oct. 1957-March 1958 period, excess deaths in the US, numbered 62,000[9]. In the three-month period February-April period in 1963, excess deaths numbered 57,000. In these two instances, excess deaths were 36 and 30 % higher than "normal". In the US, at the peak of the COVID crisis March-May 2020, excess deaths were 122,300 and Covid deaths around 95000. Expected deaths – around 660,000 so excess deaths were about 18 %. Eighteen percent too many deaths but what did the US do to confront the nearly double excess death crisis in both 1957-58 and 1963?

It did absolutely nothing. Apart from the severity of the disease, there are other remarkable similarities between the two years. In a rather detailed article, David Henderson [2009]

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[8] Somewhat disquieting is the Covid infection death rate in China compared to the rest of the world, including the US. The infection death rate in China, as of September 30th was 5.2 %, and this placed it at the 90th percentile of infection death rates. On the same date, US Covid infection death rate was 2.9 %, very close to the world average of 2.7 %.

[9] Excess deaths represent the difference in actual deaths versus expected trend deaths at that point in time (day, month, year, etc.).

documents the debate and events around the flu epidemics of the 50s and 60s. The late David Henderson was a leading authority/administrator of his time, comparable to Anthony Fauci in 2020. It is worth quoting Henderson in some detail, primarily to understand the uncanny similarities with today. Henderson was comparing 1957-58 with the 2009 flu pandemic – the reader can mentally substitute 2020 with 2009.

(a) Comparison between 1957-58 and 2009 flu epidemics (and 2020 pandemic)

"Both arose early in the year and spread widely during the spring. While outbreaks substantially abated over the early summer months in the northern hemisphere, major epidemics developed in the southern hemisphere (the traditional seasonal pattern). To date, the reported clinical presentation of cases and transmission of disease appear to be similar to and be reminiscent of the 1957 pandemic outbreaks. Of the patients requiring hospitalization in 2009, many have been reported as having underlying medical conditions." (Henderson et. al. 2009, p.1)

More details on what happened in 1957 – and the lack of panic, or demand for stringent controls, let alone a lockdown, then vs stringent lockdowns today.

"During the 1957 pandemic, 25% of the U.S. population became ill with influenza, and excess mortality due to pneumonia and influenza occurred. *The 1957-58 pandemic was such a rapidly spreading disease that it became quickly apparent to U.S. health officials that efforts to stop or slow its spread were futile.* Thus, no efforts were made to quarantine individuals or groups, and a deliberate decision was made not to cancel or postpone large meetings such as conferences, church gatherings, or athletic events for the purpose of reducing transmission.

No attempt was made to limit travel or to otherwise screen travelers. Emphasis was placed on providing medical care to those who were afflicted and on sustaining the continued functioning of community and health services. *The febrile, respiratory illness brought large numbers of patients to clinics, doctors' offices, and emergency rooms, but a relatively small percentage of those infected required hospitalization.* (emphasis added).

Note that 25 % of the population today would be close to 85 million (hypothetically or equivalently) suffering from influenza and without adequate vaccine – yet no lockdowns. That many people were affected by influenza. In addition, a comparison with the *bad* flu epidemics of previous years yields the unexpected result that while COVID is deadly, it is not as deadly as widely feared.

Much is known about influenza and pneumonia, and vaccines are readily available. An important difference with influenza is that one can be infected by COVID19, and yet not show any symptoms. Therefore, unless one is tested, asymptomatic cases may fail to register in the Covid counting. If the fatality rate is deaths per case (Case Fatality Rate or CFR), then as the denominator rises due to more cases being counted, the ratio falls. Seroprevalence of SARS-CoV-2 is estimated to be between 6 to 24 times the actual number of cases; "for 7 sites (Connecticut, Florida, Louisiana, Missouri, New York city metro area, Utah, and western Washington state) " the estimate was more than 10 times the actual cases(JAMA, July 2020).

Anand et. al. (Sept. 25, 2020), found that

"during the first wave of the COVID-19 pandemic, fewer than 10% of the US adult population formed antibodies against SARS-CoV-2, and fewer than 10% of those with antibodies were diagnosed".

Given an adult population upwards of 250 million, ten percent translates into more than 25 million. When the final count is made, it is likely that the number of millions infected by COVID19 (including asymptomatic cases) would be in the 50 million plus range for the US, or about 5 times the current number of infections.

The antibodies infection to actual case ratio has fallen drastically between June and September – a result very likely due to increased and intensive testing. For the 2018-19 flu season, and with abundant availability of a vaccine, about 35.5 million still contracted flu, and there were 34,200 deaths, with more than 25,000 deaths in the 65+ age category.

The flu fatality rate, with vaccine, is approximately one tenth of 1 % of the population infected (ratio of 34000 and 35 million). For the 2020 COVID season, the COVID fatality rate is likely to be (250,000 as a ratio of 50 million sero-prevalent cases) or five-tenths of 1 % i.e. five times higher than influenza, but still much lower than commonly assumed.

Given this broad comparability between a bad flu season and COVID19, the questions remains – did this new pandemic require extensive lockdowns across the world? More importantly, did the lockdowns *reduce* the number of infections than would have occurred without lockdowns? The next five sections of the paper concentrate on the answers to these important questions.

**Section 3 – Data and Methods**

The effectiveness of containment policy across *countries* is examined via a multi-country dataset. Data until Sept. 30 2020 are examined, and for a sample of more than 160 countries.[10] These data are used both as a panel *and* as individual country data. The important sources of data: the John Hopkins University data on virus cases and deaths; European Commission data, which provides data from December 31st and updates it on a daily basis (via an excel file); the Our World in Data for Covid tests[11]; the Oxford University Tracker data on containment (or restraint) measures undertaken by various governments across the globe; and the ACAPS data on lockdowns. In addition, population data were obtained from the UN, the macro data from the IMF, and social demographics data from the World Bank. Detailed data was assembled for 194 countries; for 161 of them, diffusion models were estimated, covering more than 99 % of the world population.

*Stringency Index:* There are **8** forms of containment measures (versions of lockdown) meticulously documented for every country by a team of scholars at Blavatnik School of Government at Oxford University (hereafter OxCGRT). Closure of schools (C1), closure of office spaces (C2), closure of public events (C3), restrictions on the size of public gatherings (C4), closure of all forms of public transport (buses, metros, trams, etc.) (C5), stay at home requirements (C6), restrictions on internal movements within a country (C7), and restrictions (bans) on international travel (C8). From these indicators, Blatinvik et. al. construct a composite index of containment which they call the Stringency Index (SI).

To capture the possibility of non-linear effects of SI on diffusion, we use variations in it to construct **6** separate representative stringency-based indices of lockdown. This is to capture "intensity" of containment; the assumption being that more the stringency, more the effectiveness of lockdown (as argued in the October 2020 WEO report of the IMF). There are four cut-off points with the measure being "on" if the index (which is scaled from 0 to 100) being greater than 39, 61,

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[10] Over 200 countries/regions have experienced at least one virus case; our 140 odd countries is lower because many countries had very few data points for cases, or deaths, or both. In addition, some country data like Vietnam does not show a "consistent" or estimable pattern. For example, the number of cases in Vietnam stayed at 16 for almost an entire month starting February 13, and then stayed around 250 for almost the entire month of April.

[11] Incidentally, this data set does not report on any Covid tests being conducted in China.

75, and 85 (less than 39 constitutes the first range). In addition, extreme stringency is defined as index in the range 75 to 100. There are thus 14 possible containment measures. A **15$^{th}$** SI variable is the SI itself.

The individual eight stringency measures lead to the creation of non-overlapping **8** *sums of containment* measures for each country. Each of the measures is scored 1 when it is operational and zero when not. At any point in time, anywhere from 0 to 8 measures are operational. These sums do not, and cannot, identify which one, two, three or four etc. containment policies flatten the growth curve; but the method can identify whether more restrictions are better than fewer. The results suggest that fewer restrictions lead to less infections.

*Lockdown:* The ACAPS data contains, on an intermittent basis, the imposition of either a partial, or a complete, lockdown. We construct *3* lockdown variables as follows. In the first stage, the three lockdown variables - partial lockdown (L1), full lockdown (L2), and either partial or full (L3). These intermittent lockdown variables are combined with the OxGRT stringency index to yield additional indicators for lockdowns. For example, L0, is constructed as follows. It is set equal to the ACAPS full lockdown variable. If this data does not exist, then a full lockdown is defined to be if the stringency index exceeded 75, failing which a stringency index greater than 61. And failing this, lockdown is defined to be the partial lockdown ACAPS definition.

Hence, we have **26** different representations of policy for each country-day. We estimate models for **12** regions of the world – 7 broadly geographic World Bank regions (e.g. South Asia, East Asia, Eastern Europe etc.), region 8 being all countries in the world, regions 9 and 10 countries classified by population size (less than or greater than 10 million), and regions 11 and 12 countries classified by low or high per capita income [a country is high income if its per capita dollar income was above $15000 in 2019).

It is expected that the 26 different definitions of closure, and 12 different regions, account for all the possible data and information non-linearities that maybe present in the COVID world. The goal is to identify patterns in large numbers of observations, and combinations.

*Timing of Containment Policies*

No stringency data are available for 19 countries/regions of the world and these contain approximately 12 million people. Armenia is the highest population economy in the group with no lockdown measures according to ACAPS data, and no stringency index value according to the OxGRT data.

What is striking about the containment measures is first, their universality, and second, the date of the interventions – Tables 1a and 1b, respectively.

**Table 1a: Number of Countries with OxGRT Restrictions on**

| Date | Schools | Work | Public Events | Gatherings | Public Transport | Stay at Home | Internal Mobility | Border Closures |
|---|---|---|---|---|---|---|---|---|
| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
| 29-Feb | 16 | 4 | 14 | 6 | 2 | 2 | 4 | 94 |
| 9-Mar | 37 | 6 | 36 | 22 | 3 | 3 | 9 | 115 |
| 15-Mar | 114 | 46 | 100 | 84 | 32 | 17 | 28 | 151 |
| 24-Mar | 161 | 116 | 152 | 139 | 90 | 74 | 89 | 169 |
| 31-Mar | 167 | 144 | 162 | 156 | 120 | 101 | 122 | 170 |
| 15-Apr | 170 | 151 | 166 | 160 | 133 | 119 | 133 | 172 |
| 30-Apr | 170 | 151 | 166 | 160 | 131 | 116 | 125 | 172 |

**Table 1b: Total Population with OxGRT Restrictions on**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 15-Feb | 1876 | 1439 | 1535 | 1428 | 1428 | 1428 | 1524 | 3749 |
| 29-Feb | 2257 | 1500 | 1895 | 1654 | 1431 | 1489 | 1589 | 5837 |
| 9-Mar | 4491 | 1507 | 2698 | 2005 | 1439 | 1630 | 1867 | 6168 |
| 15-Mar | 6197 | 2219 | 5983 | 3914 | 2284 | 2276 | 2227 | 6955 |
| 24-Mar | 7445 | 6189 | 7289 | 6581 | 5593 | 4917 | 5612 | 7428 |
| 31-Mar | 7495 | 6810 | 7351 | 6886 | 5189 | 5708 | 6652 | 7433 |
| 15-Apr | 7525 | 7108 | 7385 | 7188 | 5393 | 4915 | 5374 | 7438 |
| 30-Apr | 7526 | 7118 | 7343 | 7204 | 5389 | 4788 | 5448 | 7438 |

Source: OxGRT, World Bank (population data)

According to OxGRT data, at the end of February, there were only 16 countries that had closed schools; by March 11$^{th}$, the day of the WHO pandemic announcement, the number of countries doing so had jumped to 54; four days later, the number of countries/regions had nearly doubled to 114; by March 24$^{th}$, there were 161 countries. Of particular interest are the data for border closures (C8), the primary transmission mechanism for the virus, given that it originated in China. Even as early as February 1st, 57 countries had closed their borders; by February 23rd , 85 countries had already done so, or 4.2 billion, or close to 70 % of the world's population excluding China.[12] A day before the WHO announcement of the pandemic on March 10th , 115 countries had already closed their borders (comprising 6.2 billion people).

Correlations among the eight containment variables, as of April 15 (when 189 countries had at least one reported case, and there were a total of 2 million infections or only 11 % of the infections as of July 31st )[13] are reported in Table 2. Three containment policies (public transport, stay at home requirements, and restrictions on internal movements) have a cross-country correlation with school closures ranging from 0.78 to 0.86; for the remaining five containment measures, the correlation is above 0.9!

**Table 2: Correlation Matrix of Number of Countries with restrictions**

| Closure of | Schools | Work | Public Events | Gatherings | Public Transport | Stay at Home | Internal Mobility | Border Closures |
|---|---|---|---|---|---|---|---|---|
| Schools | 1 | | | | | | | |
| Work | 0.92 | 1.00 | | | | | | |
| Public Events | 1.00 | 0.94 | 1.00 | | | | | |
| Gatherings | 0.98 | 0.97 | 0.99 | 1.00 | | | | |
| Public Transport | 0.83 | 0.98 | 0.87 | 0.93 | 1.00 | | | |
| Stay at Home | 0.78 | 0.96 | 0.83 | 0.90 | 0.99 | 1.00 | | |
| Internal Mobility | 0.86 | 0.98 | 0.89 | 0.93 | 0.99 | 0.98 | 1.00 | |
| Border Controls | 0.97 | 0.82 | 0.96 | 0.95 | 0.77 | 0.72 | 0.79 | 1.00 |

[12] China closed its international borders (outgoing and incoming flights) on February 24th, when total cases in China had reached 77,749, a level very near its final level of around 90,000 cases. For most countries, closure of international borders was the fastest, and the first act, and when cases were in their teens, and hundreds, and near the beginning, and not the end, of the virus.

[13] We estimate the effect of lockdowns broadly for data until July 31st, since both the reopening of economies, and the advocacy and presence of testing "contaminates" the diffusion data post July 31st. Note that these exclusions of data bias the results in *favor* of lockdowns being effective in containing the virus.

These correlations are very high and confirm the fact that many were implemented simultaneously. A large majority, close to universality of containment-was-successful papers, have attempted to attribute *individual* separate estimates of the effectiveness of policies. As we will show in the next two sections, these estimates are even more problematical with the perspective that the aggregate of containment polices were only successful in a small minority of countries. Further, containment policies very likely had a perverse effect on infections (i.e. led to an increase relative to a no containment strategy) for more than three-fourths of the sample of countries.

These results seem counter-intuitive, especially in the context of lockdowns everywhere. But consider the following facts about Covid, albeit at a heuristic level. WHO director, Mr. Tedros, said as early as March 11, that history does not have a precedent for control of a pandemic. End March 2020, 170 countries had closed their borders, 140 countries had six or more of the OxGRT containment measures in place, the average stringency index was 69.3, and there were 881000 COVID cases and 43,000 deaths. With lockdowns, cases were expected to reach their terminal level perhaps ten times higher at 8.8 million?  Today cases are 40 times, and deaths 24 times, higher. This has occurred during the most intense period of lockdowns and controls around the world. These are not statistics about even partial success.

How the world thought that lockdowns would control the pandemic is a subject that should, and will, receive increased scrutiny in the future.

## Section 4: Were Lockdowns Effective in Containing the Spread of COVID19 ?

Lockdowns are meant to change the shape of the diffusion curve; hence, the popular use of the term “flattening the curve”. Lowering of the growth rate of infections is a key goal of lockdowns, and other containment policies. Herd immunity policy, as followed by Sweden, also aims at lowering the growth rate of infections; as have all anti-infection policies to date, including the anti-influenza pandemics of the late 1950s.

What is new, however, about the fight against Covid is the highly innovative policy of lockdowns to achieve closure on the virus. As documented in Section 2, this radical view was encouraged by early reports of the success of lockdown policy from Wuhan, China, the city of origin of the new virus.

*Universal Pattern of Diffusion – The S-shaped curve*

Diffusion patterns are obviously non-linear and hence the concentration in virus models has been on estimation of non-linear growth equations. One common empirical method is to estimate a growth equation via an ARIMA (auto-regressive integrated moving average) process. A more common, and useful, procedure is to estimate a logistic growth equation. This is the S-shaped curve and estimation of S-shaped curves has a long history in both virology and economics. Zvi Griliches (1958) was the first to estimate a S-shaped curve in his study of the diffusion of hybrid corn in the US in the 1950s. Almost 200 years ago, Gompertz(1825) employed an S-shaped formulation to estimate patterns of mortality. Bhalla(2012) estimates an S-shaped curve to document the relationship between the real exchange rate and per capita income.

A diffusion curve for most viruses (and adoption of innovations, and much else) is characterized by a three-part pattern: a flat to slowly rising part in the beginning, an accelerating part in the middle, and a decelerating to once again flat part at the end when the number of cases is no longer changing. (See Figures 2(a) and 2(b)).

The Gompertz and Logistic equations represent the S shape well, and their representations are as follows:

$$\text{Logistic} \qquad z = K/(1 + e(-r * (t - I))) \qquad (1a)$$

$$\text{Gompertz} \quad z = K{*}e\big(-e\big(-r * (t - I)\big)\big) \tag{1b}$$

Each equation (S-shaped pattern) involves the estimation of three basic parameters – the average rate of growth of diffusion *r*, the inflection point *I,* and the ceiling level *K*. The inflection point is the level (unit of time) where the growth rate reaches its peak. After this point, the growth rate of infections begins to decline towards its ultimate destination of zero (end of the pandemic). The logistic curve estimate of *I* has the property that it represents the half-way point of the diffusion i.e. the number of days post the inflection point is equal to the number of days taken to reach this point. In the case of the Gompertz curve, *I* represents the point where the virus reaches approximately 36.8 percent of its final (*K*) value.

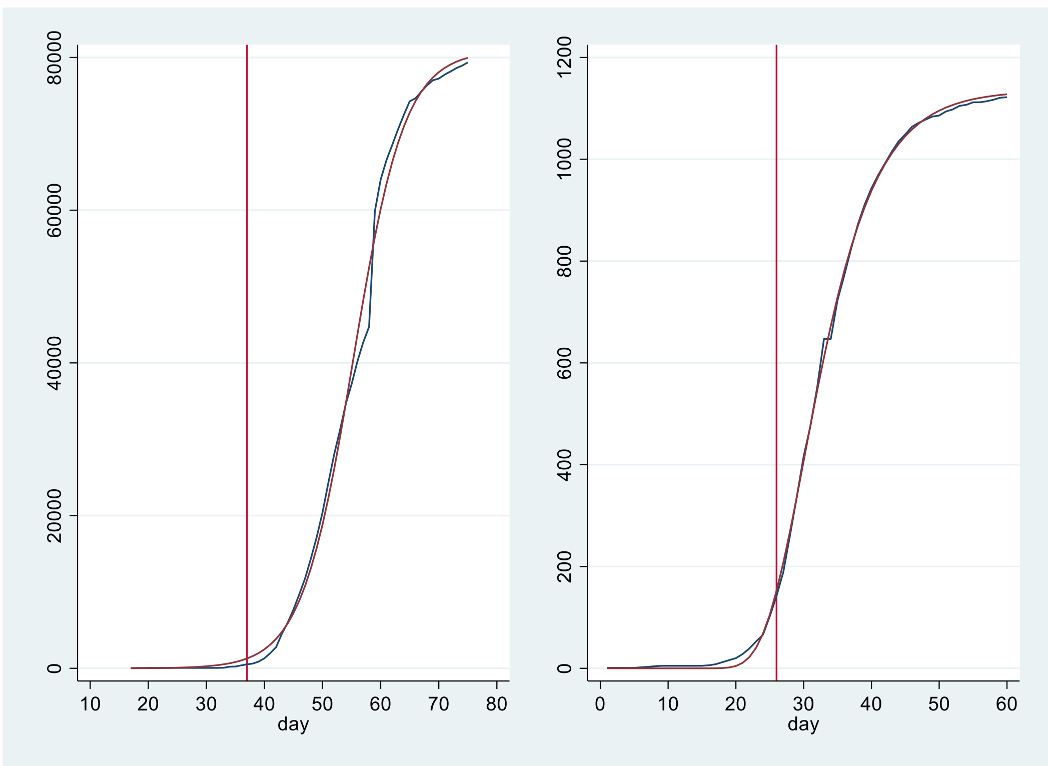
Note that the logistic is a near definitional S in that at the start of the spread of the virus there are a few number of cases (the left flat portion of the S). As the virus spreads, the cumulative number of cases accelerate, and the middle portion of the S becomes stretched and bent forward i.e. an elongated middle and non-backward bending S! Thus, the Gompertz is no more than an elongated, or a stretched out version of the logistic. This means that the average rate of growth *r* yielded by the two models are not comparable with the logistic *r* being higher than the Gompertz *r*. Estimates of ceiling *are* comparable for both models i.e. *K* represents the cumulative infections at the end (time equal to infinity).

*Gompertz or Logistic?*

In over several hundred comparisons (more than 150 countries, more than 12 different time-periods, and separate estimates for Covid infections and Covid deaths), we find that the Gompertz equation is more accurate. The accuracy is largely determined by the value of the $R^2$ though in both models the $R^2$ is generally above 0.99. Time-series models are expected to yield high $R^2$; however, a simple quadratic, or extensions thereof, models fail to exceed an $R^2$ beyond 0.9. For more than three-fourths of the models, the Gompertz curve outperforms the logistic curve, and outperforms in both R-squared *and predictive accuracy of the terminal value*. We had mentioned the importance of Gompertz in our blog (Bhalla-Virmani June 6 Blog 4)[14].

Figure 2 below shows the diffusion of COVID cases for two countries at comparable times (days since the first virus case rather than calendar time). The length of time considered is sixty days of experience with the virus. The two countries are China and New Zealand; the red line is the day of lockdown.

Figure 2(a) China - Logistic 2(b) New Zealand – Gompertz




Notes: For China, day 1 of the virus is assumed to be Dec. 15, 2019. Red lines denote the day of lockdown.

[14] "Most investigators have used the logistics curve to represent this pattern. We find that for COVID19, the Gompertz curve provides a better approximation of the elongated S than other logistic curves." Blog 4.

*Rate of growth of infections and R0*

Epidemiologists (now a household word) estimate the progress of infections via a transmission model. The transmission model has an acronym SIR: Susceptible – those that can potentially get the virus; I the number of infections and R those removed either through death or recovery

The key "result" of such a transmission model is the basic reproductive number R0, defined as the expected number of additional cases that each infection will generate, on average, over the course of its infectious period. If R0 is greater than 1 each infected person is likely to transmit the virus to more than 1 person; after this point, each infected person will affect only 1 person. Eventually, the multiplicative transmission process ends when no more new cases are identified.

Estimation of R0 is reasonably precise at the end of the virus because by then all the parameters of the model are known. Unfortunately, COVID-19 has been a shifting virus which has surprised most by having several false "endings" i.e. R0 can stay low for long periods of time, and then rise again, as has now happened for many economies, including the US. For example, R0 for the US was steadily declining till it reached 1.082 in mid-June; from there it steadily increased to 1.147 (mid-July) and end-Sept it was around 1.04, and now (late October) it is close to 1.07.

*Alternatives to R0 estimation*

Wallinga and Lipsitch (2007) show how there is a simple relationship between R0 and the rate of growth of infections. If the average duration of incubation of the virus is known (defined as $T_c$ and estimated to be around 7.5 days) then R0 is given by [15]

$$R0 = 1 + r^* T_c \qquad (2)$$

Analysis of the effectiveness of interventions has proceeded generally around the examination of trends in R0 (i.e. did the intervention reduce R0) or around the growth of infections (was the growth post-NPI less than the growth pre-NPI). As shown by the R0 equation, interpreting the trend in R0 is equivalent to interpreting the trend in *r*. It is true that a reduction in R0 is a

[15] Note that in this equivalence, the terminal value of R0 is equal to 1 when r equals 0

necessary condition for success – it needs to be examined is whether that is sufficient. This is an empirical question.

The conclusion "growth rate of infections declined with interventions" is not very informative. A recent article by Tufecki (Sept 30, 2020) documents, in detail, the flawed nature of R0. Even in the normal course of events (let us call it the Swedish model) the growth rate will eventually decline. Whether one intervened early with interventions, or late, at some point post the intervention, the growth rate is lower. The same problem exists with studies about R0.

*False positives – r declines but K increases*

A large part of the Covid-lockdown research has concentrated on showing that *r* declined post lockdowns. This research assumes that there is no relationship, or at best a weak relationship between *r* and K. Only if this were the case could one confidently conclude that a lower *r* was a meaningful indicator of success.

However, there is a systematic negative relationship between the estimated percentage change in ceiling (K) estimates, and estimates of the rate of growth *r*. And there is a negative relationship between r and the duration of the virus (proportional to I). Table 3 reports the data for the Gompertz curve for different time-periods of estimation.

**Table 3: Changing Estimates of Gompertz parameters**

| | % Change in log Ceiling K (%) | mean r(%) | mean I(days) |
|---|---|---|---|
| data ending on | | | |
| 15-Apr | 37.1 | 8.3 | 43 |
| 30-Apr | 46.2 | 6.7 | 52 |
| 15-May | 40.8 | 6.4 | 57 |
| 31-May | 35.9 | 5.9 | 67 |
| 15-Jun | 34.8 | 5 | 78 |
| 30-Jun | 39.6 | 4.6 | 89 |
| 15-Jul | 19.5 | 4.3 | 92 |
| 31-Jul | 8.7 | 3.9 | 95 |
| 15-Aug | 24.4 | 3.4 | 105 |

Notes: The first period of estimation ends on March 31; model estimates for 143 countries

This has important relevance for research showing that lockdowns decreased r (or equivalently that lockdowns decreased R0). The explanation was that lockdowns worked because the growth rate declined – but if the growth rate decline was accompanied by a significant increase in total number of infections then it is not convincing evidence that lockdown worked.

High negative correlations between r and K (more accurately between the log change in ceiling K and the average rate of growth estimated for the same country but across different time-periods) suggest that it is inappropriate to assume that a decline in the growth rate of the virus had no effect on the terminal value (K) of the virus.[16] Given the close relationship between R0 and r it also follows that models documenting a decline in R0 as an indicator of success of the lockdown reached a hasty and inaccurate conclusion.

Not emphasized enough in the curve flattening discussion is also the fact that there is an inverse relationship between the average rate of growth and the estimate of the duration of the epidemic ( e.g. 2*I in a logistic equation). What really matters is that the flattening is achieved by policies which do *not* increase the value of *K*, and preferably lower the ceiling level from the counter-factual case of no policy intervention. The herd-immunity model is the real counter-factual to an NPI model; and according to it, the ceiling K is lower when there are no interventions in the "natural" process of virus diffusion.

**Section 5: Gompertz curve and policy interventions**

The Gompertz model has an additional advantage (besides an impressive ancestry and excellent explanatory powers). The first derivative of the log of a Gompertz equation is of a closed nature and hence easy to estimate – and relatively straightforward to incorporate the effects of additional determinants of diffusion e.g. lockdowns.

[16] There is an intuitive reason for there to be an inverse relationship between r and I (for the same ceiling, a lower growth rate means longer duration). If the ceiling does increase significantly, and if there is convergence, then on most occasions the increased ceiling is achieved with a lower growth rate.

Let any policy (intervention) measure be indicated by P, and its effect be captured by the expression ($\delta_0$ + $\delta_1$ *P*t), where $\delta_0$ and $\delta_1$ are constants, P is the policy measure (e.g. a dummy representing school closures).

The Gompertz equation (1b) can then be represented by

$$z_i = K_i e^{-e^{-r_i(t-I_i-\delta_{0i}P-\delta_{1i}Pt)}} \qquad (3)$$

where $Z_i$, $K_i$, $r_i$ and $I_i$ represent the cumulative number of cases, estimated (terminal) ceiling value, estimated average growth, and inflection level (in unit time) respectively for country $i$.

Taking log on both sides

$$\ln(z_i) = \ln(K_i) - e^{-r_i(t-I_i-\delta_{0i}P-\delta_{1i}Pt)} \qquad (4)$$

Taking derivative with respect to $t$, one obtains

$$m_i = \frac{dln(z_i)}{dt} = -[-r_i + r_i\delta_{1i}P]e^{-r_i(t-I_i-\delta_{0i}P-\delta_{1i}Pt)}$$

where $m_i$ is the growth rate.

Taking log on both sides yields

$$\ln(m_i) = \ln(-[-r_i + r_i\delta_{1i}P]) - r_i(t - I_i - \delta_{0i}P - \delta_{1i}Pt)$$

Simplifying and rearranging

$$= \ln(r_i) + \ln(1 - \delta_{1i}P) - r_i(t - I_i - \delta_{0i}P - \delta_{1i}Pt)$$

If $|\delta_{1i}| < 1$, then by log approximation

$$\ln(m_i) = \ln(r_i) - \delta_{1i}P - r_i t + r_i I_i + r_i\delta_{0i}P + r_i\delta_{1i}Pt$$

Rearranging again

$$\ln(m_i) = [\ln(r_i) + r_i I_i] - r_i t + (r_i\delta_{0i} - \delta_{1i})P + r_i\delta_{1i}Pt$$

Or

$$\ln(m_i) = A_i + \beta_{1i}t + \beta_{2i}P + \beta_{3i}Pt$$

where $A_i = [\ln(r_i) + r_i I_i]$;  $\beta_{1i} = -r_i$;  $\beta_{2i} = (r_i \delta_{0i} - \delta_{1i})$; $\beta_{3i} = r_i \delta_{1i}$

Adding an error term $\epsilon_{ij}$ yields the regression equation with $i$ representing country and $j$ representing time.

$$\ln(m_{ij}) = A_i + \beta_{1i} t_{ij} + \beta_{2i} P_{ij} + \beta_3 t_{ij} P_{ij} + \epsilon_{ij} \qquad (5)$$

In equation (5) the dependent variable is the log of the growth rate, and the coefficients measure the average impact; a fixed-effect model yields individual country estimates of $A_{i.}$ $P_{ij}$ is a dummy variable whose value is zero when no intervention, and one during the days of lockdown (NPI).

If lockdowns are effective in reducing the growth rate then the coefficient $\beta_3$ is expected to be negative, and significant i.e. intervention lowers the growth rate of infections, or deaths. This test was mentioned at an IMF seminar on COVID diffusion in mid-June (Bhalla-Virmani (2020b)); Virmani(2020) presents several results of this "test"; and Harvey-Kattuman(2020) were one of the very early advocates of the Gompertz curve for the study of Covid diffusion.

*Problems of Mis-Specification and multi-collinearity*

Equation (5) is mis-specified if there are multiple intervention variables (as was most manifestly the case in the case of COVID). Assume that there are only two containment policies – school closings ($P_1$) and workplace closings ($P_2$). Both $P_1$ and $P_2$ are dummy variables representing when the policy is on ($P_1$, $P_2$ equal to 1) and when neither policy is in place ($P_1$, $P_2$ both equal to 0). Assume for a moment that for a country C, policy $P_1$ is implemented on day 25 and policy $P_2$ is implemented on day 35. If a regression is run with just $P_1$, then until day 34 it will yield the right answer and reflect the impact of policy $P_1$ on the (log) rate of growth of infections; but from day 36, the coefficient of $P_1$ will include the effect of policy $P_2$ as well i.e. a specification error (or omitted variable bias).

One way of estimating the unbiased coefficients of $P_1$ and $P_2$ is to run the model with four dummies representing the four states possible: (0,0), (0,1), (1,0) and (1,1). But with eight containment variables the number of dummies that need to be included is 64 – an inelegant computation whose interpretation would be too confusing.

Note that the above estimation problem pertains to both specification (when the estimating equation has either $P_1$ or $P_2$ but not both) and multi-collinearity (when all 4 dummies are in the model (correlation between the states of (0,1), (1,0) and (1,1)).

Is there a solution to this estimation problem? None if the goal is to estimate the *separate* effect of school closures and workplace closings (as estimated by Dergiades et.al., Deb et.al., Eckhardt et. al, and many others). Conclusions based on these partial estimations are not unbiased. But if the goal is to determine whether a *combination* of containment policies had an effect, then that goal can be reached. For each time period t, one can sum up all the containment polices in place in each country. This sum (*Sum1to8*) will range from 0 to 8 – zero when no containment policies are in effect, 2 when only 2 (can be any two) are implemented, and eight when all eight are implemented. Eight different dummies are then formed with Sum1 equal to 1 when only 1 policy was on, to Sum8 equal to 1 when all eight are on.

The dependent variable is the log of the country-specific growth rate at any point of time. Equation (5) above can be used to derive estimates of the effect of policy interventions on the growth rate. However, as is obvious from our earlier discussion, a negative effect of the policy on the growth rate ($\beta_3 < 0$ in equation (5)) need not mean that the policy succeeded.

Nevertheless, most research on the lockdown effectiveness has concentrated on documenting the trend in the growth rate, and we do the same below. Some findings in the literature: Dergiades et al find that the effectiveness of government interventions in slowing or reducing deaths is higher the earlier and more "stringent" the interventions. This is also the result reached by the IMF WEO, as well as by Amuedo-Dorantes et. al. (for US states; Spain), amongst others.

Bonardi et al look at infection growth rates and policies, and find that internal restrictions are more effective than external. They also find that lockdown measures were statistically significant in developed countries but not in developing countries. This result is also consistent with our findings – see next Section.

Deb et al. find that containment measures are highly effective in flattening the pandemic curve, with two different patterns. First, that infection growth falls sharply and stabilizes for 10-15 days after containment, but later creeps back up to the level without containment measures. Their second result is that there is a gradual reduction in the infection growth rate, a trend which persists for 30 days. The also find that fast interventions have a greater effect than slower ones. We explicitly test for the speed of intervention (difference in days between the first case and date of intervention) in Section 7.

Two studies using German data show that lockdowns (social distancing bans) came too late in flattening the curve, or had very little effect. Using county level data, Wieland finds that for 412 counties (66 % of the total population of Germany, COVID-19 infections "had already decreased before forced social distancing etc. (phase 3 of measures) came into force (March 23, 2020)" (p.11). Berlemann and Haustein study three waves of containment measures in Germany and find that only the first wave (prediction for one week post the first wave announcement measures on March 8) was effective. (p. 92).

Also dissenting from the general narrative-conclusions is Meunier. In a study of Western European economies, he concludes: "our results show a general decay trend in in the growth rates and reproduction numbers two to three weeks before the full lockdown policies would be expected to have visible effects. (p. 6).

In summary, notwithstanding very few disagreements, the dominant strain in the literature is that regardless of the specification in the model, lockdowns and stringent regulations were effective in beating down the virus, slowing its spread, and most importantly, in saving lives. These are substantive conclusions which we examine in a comprehensive fashion in the rest of the paper.

*Endogeneity of Lockdowns:*

It can be argued that governments were more likely to impose restrictions when the epidemic was becoming more severe. There are two aspects to this important econometric concern, and how it is addressed. First, as the data in Tables 1A and IB abundantly the imposition of restrictions was early and simultaneous across the world i.e. countries did not wait for the epidemic to be severe before imposing restrictions. And if simultaneity were there, we address it like the rest of the literature addresses it - intervention measures are assumed to affect with a 7 day lag for infections, and a 14 day lag for deaths. Introducing policy interventions with a lag should, at least partially, address concerns about endogeneity of policy response. The effect of testing and re-opening of economies on infections is minimized by stopping the analysis on July 31.

Other attempts at controlling for endogeneity involve (e.g. WEO 2020) the examination of the effects of *national* lockdowns in regions with limited Covid infections i.e. looking at infection dynamics in regions where endogeneity is unlikely to be a problem. However, such a method may yield biased estimates of the effects of lockdowns since the dependent variable (growth in cases) would be censored from above.

*Policy Interventions and Covid Diffusion – The Evidence*

We report in Tables 4-6 several tests of the proposition that policy interventions worked (or did not work). In total we examine 25 different definitions of containment; across 12 regions of the world, and for two different definitions of the dependent variable – log growth of infections, and log growth of COVID deaths.

The goal is to test for the coefficient of the policy variable – if it is negative, then the conclusion is that the intervention caused, or was associated with, a decline in the rate of growth of infections (or deaths). For each intervention measure, there are a total of twenty-five models for each region.

***The result: regardless of whether it is infections or deaths, the success of interventions (coefficient $\boldsymbol{\beta_3}$ in equation (5) is significant and negative) is very low.***

For the world in the aggregate (Table 4) only 2 out of 25 models yielded a negative and statistically significant coefficient; the number of models yielding a perverse positive sign (i.e. intervention yielded an *increase* in the growth rate of infections) was 12. For the advanced economies, three interventions yielded a negative sign, and only one was positive. For the East Asian region (one with the largest fraction of intervention performers like China, Vietnam, Singapore, Thailand etc.) not a single model yields a significant negative coefficient; the same for the growth rate of deaths (zero significant declines and 6 out of 25 models with a significant positive coefficient!) For all the twelve regions, and all 600 models, the lockdown-is-success conclusion is reached on 50 occasions (20 for infections and 30 for deaths). This is only an 8 % success rate; a significant failure rate is double that at 16 %. In addition, for 75 % of "experiments", lockdown had no effect on the growth rate. (Table 4 has the details).

**Table 4: Impact of NPI Interventions (lockdowns) on curve flattening (decline in r)**

| Area | Models | Significant and Negative | Significant and positive | Negative - not significant | Positive - Not Significant |
|---|---|---|---|---|---|
| *Dependent Variable is log of growth rate of infections* | | | | | |
| *Region* | | | | | |
| Advanced Economies | 25 | 2 | 1 | 7 | 15 |
| East Asia | 25 | 0 | 4 | 3 | 18 |
| Europe - East | 25 | 2 | 1 | 6 | 16 |
| Latin America | 25 | 3 | 7 | 4 | 11 |
| MENA | 25 | 2 | 11 | 3 | 9 |
| South Asia | 25 | 1 | 0 | 14 | 10 |
| Sub Saharan Africa | 25 | 3 | 9 | 3 | 10 |
| World | 25 | 2 | 15 | 3 | 5 |
| Population < 10 mil | 25 | 2 | 14 | 4 | 5 |
| Population > 10 mil | 25 | 0 | 15 | 5 | 5 |
| Low Income | 25 | 3 | 14 | 4 | 4 |
| High Income | 25 | 0 | 6 | 4 | 15 |
| **World** | 300 | 20 | 97 | 60 | 123 |
| *Dependent Variable is log of growth rate of deaths* | | | | | |
| Area | | | | | |
| Advanced Economies | 25 | 1 | 2 | 11 | 11 |
| East Asia | 25 | 0 | 6 | 7 | 12 |
| Europe - East | 25 | 3 | 0 | 10 | 12 |
| Latin America | 25 | 2 | 2 | 11 | 10 |
| MENA | 25 | 4 | 2 | 3 | 16 |
| South Asia | 25 | 2 | 2 | 8 | 13 |
| Sub Saharan Africa | 25 | 3 | 0 | 5 | 17 |
| World | 25 | 3 | 11 | 6 | 5 |
| Population < 10 mil | 25 | 3 | 1 | 5 | 16 |
| Population > 10 mil | 25 | 3 | 13 | 5 | 4 |
| Low Income | 25 | 3 | 11 | 3 | 8 |
| High Income | 25 | 2 | 7 | 6 | 10 |
| **World** | **300** | **29** | **57** | **80** | **134** |

*Note: For curve flattening to have been achieved, the coefficient of the policy intervention the variable in equation 5 has to be significant and negative.*

Table 5 lists the equations (regions, interventions) that did reveal a significant, and negative, policy effect ($i.e.\ \beta_3\ negaive$ – intervention worked). Note that these estimates do not suffer from the problem of either multi-collinearity, or specification error. These are fixed effect regressions and control for individual country effects (as done by others).

**Table 5: Which Interventions Really Matter**

| | | *Negative & Significant* | |
|---|---|---|---|
| | # Tests | Infections | Deaths |
| Strict Lockdown | 12 | 1 | 0 |
| Sum I = 1 | 12 | 5 | 9 |
| Sum I = 2 | 12 | 4 | 7 |
| Sum I = 3 | 12 | 2 | 1 |
| Sum I = 4 | 12 | 1 | 0 |
| Sum I = 5 | 12 | 1 | 1 |
| Sum I = 7 | 12 | | 1 |
| Stringency Index 1 | 12 | 5 | 9 |
| Stringency Index 4 | 12 | | 1 |
| Stringency Index 5 | 12 | 1 | |
| Models | 300 | 20 | 29 |

*Notes: Sum I refers to the number of infections in place. Higher the number next to Index, more the stringency .*

Note that a large proportion of the measures yielding the desired slowdown in growth rates post intervention are of the low intensity of interventions variety. For example, in Table 5, a strict lockdown lowered the growth rate in only 1 out of 300 tests; less than two interventions and stringency index 1 (when OxGRT index value is less than 39) reduced the growth rate in 39 of the 49 cases (infections and deaths!).

The results on the impact of interventions on the growth rate as presented above are in the same spirit as most of the NPI evaluations of COVID. But, as we have emphasized throughout, such results are tentative, at best, in rejecting the hypothesis that interventions worked. The fixed-effect cross-country regressions suffer from the usual drawbacks (they capture just the average effects despite control for time, temperature, and other “fixed” country effects).

**Section 6 – Direct Test of the Effect of Interventions**

What is needed, required, is a *direct* method of estimating the effect of NPI's on cases and deaths. An early attempt towards this goal was provided by Harvey-Kattuman for Great Britain and Germany. Some others (Wieland, Meunier) have estimated individual diffusion curves for selected countries (e.g. Germany). These papers were published in the early days of the virus and were the exception to the rule that interventions were "good" or that NPI's yielded positive results.

The results presented in this section might be the first to estimate *individual* patterns of COVID diffusion for many countries (equaling 143). This allows us to estimate the time-profile of diffusion before and after interventions. Time is measured in the number of days elapsed since the country first registered 10 or more cases (this to reduce noise in the estimation when data points are low for each country). We stop the "clock" for most countries around July 31$^{st}$ and August 15 (somewhere around day 155 from the day the 10$^{th}$ case was registered; the reason for a non-precise date is because the 10$^{th}$ case was registered in different countries on different dates). This top "censoring" is done for two important reasons, both of which bias the results towards showing that lockdown worked. The two reasons are testing and the re-opening. With testing has come an increase in the infections reported so including data post testing will bias the results towards showing that lockdowns had little effect. Ditto for re-opening because there maybe a possibility of a rise in infections because of the re-opening – again, biasing the results on effectiveness of lockdowns.

At its core, our direct method involves (i) incorporation of when an intervention (e.g. lockdown) was introduced (time = *t*); (ii) estimating the past and future path of diffusion as *of that date* via a Gompertz diffusion curve; and (iii) comparing the predictions of the change in cases at time *t* (referred to as benchmark or the counter-factual) with time t+h days later.

As shown in Table 1, most countries had implemented containment measures by March 31. We estimate three Gompertz equations for each country with the end data day being April 15$^{th}$, April 30$^{th}$ and May 15$^{th}$ for infections (designated as *Ha*, *Hb* and *Hc* respectively). We estimate three different point estimates for reasons of non-stability in the estimates, as well as lack of convergence in some instances. For example, when the data are estimated for Germany, the Gompertz model does not converge when the data are April 15th and before i.e. *Ha* is missing.

The first estimate (*Ha*) is selected as the representative estimate for the country if on that day there were 50 or more observations. For less than 50 observations on April 15, *Hb* is chosen, and *Hc* is chosen if *Hb* is missing (did not converge in 59 attempts). For three countries (Bulgaria, West Bank and Gaza and Slovak Republic) the average of Hb and Hc is taken as the model estimate. This procedure provides us with a benchmark counter-factual for 143 countries (approximately 7.3 billion people). [17] For the Western world, both USA and Spain are extreme outliers.

**Country Performance Indices for control of COVID**

How do we assess how different countries have performed in their fight against COVID? And what are the lessons we can learn from the successful countries? To do that, we need to define success. As mentioned above, estimation of separate models for different countries allows one to define a simple measure of success – it is the percentage difference of the actual cases from the benchmark. If the benchmark estimate is defined as H, and actual is defined as C, then the performance index is defined as (X=100x(C-H)/H). In other words, performance is defined as the percentage gap between reality(C) and forecast(H); the forecast being according to the specific baseline model estimated for that country. If the percentage is negative, it means that actual cases were less than "what would have been".

The performance index is computed for each day, and is very noisy (as would be expected). Our ranking principle is that of the Borda rank i.e. a rank of ranks. Countries are ranked according to the value of X, from smallest to highest (and X can obviously be negative though it does not

[17] The three models (April 15, April 30 and May 15) reveal model convergences for 115, 135 and 129 countries, respectively. Our final selection is of models for 143 countries. The model for Spain does a very good forecast until 150 days of the virus and then completely falls apart in its predictions. Saez et al. wrote in an April 16 paper that "the measures taken to mitigate the COVID-19 epidemic managed to flatten the curve".

happen too often, or for too many countries!)[18]. Since the benchmark estimate is as of day 50, we rank X for every subsequent day post day 50 e.g. 60, 70,…210.[19]

However, there is one more step left before finalization of ranking. In order not to bias our results, we have July 31st as the end date for lockdowns. We therefore estimate two performance indices – the first one incorporates ranks until day 160; and the second index for ranks from day 170 to day 210. We then estimate a weighted rank with weights as 11/16 for the first rank and the second as 5/16 (number of ranks for each country in each classification of time, before and after lockdown).

Obviously, many other weighting possibilities are present, and this is a subject for further research. For example, the weighting method does not give credit to countries that have recorded very few cases per unit of population. Again, a subject for further research. At this time, the goal is to assess how each country performed relative to what they were expected to perform. As many have noted, countries vary markedly in absolute levels of infection (and deaths) due to different initial conditions e.g. temperature, share of old population, urbanization, race etc. The countries are ranked according to the weighted index.

Table 6 presents the results for the top 20 countries, plus a few others of special interest (e.g. Australia, Italy, Sweden and UK). The table also presents the rank on selected days (50 which is the "base", 80 for one month ahead and 160 and 210 days). Even countries that had no national lockdown (e.g. Sweden, Japan) are included in the benchmarking, and analysis. All that is required is that the model converge! [20]

The ranking throws up a few surprises. Mexico emerges as the best performing country, with Ireland and China as second and third. Ghana is a surprise at five, and Mali is the 18th best

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[18] Only countries with population greater than 3 million are included in the rankings.

[19] Many countries are close to day 260 as of Oct 30 in terms of days elapsed since the 10th case, but the overall sample reduces substantially because of sub-Saharan economies where the virus started late. Hence, we stop at day 210 to achieve a ranking sample of 116 countries.

[20] Seven countries (Australia, Cuba, Georgia, Hong Kong , Hungary, Slovakia and Vietnam) are excluded from the rankings because of the second wave and a consequent large increase in the ranks over the two periods (until day 160, and day 160 to day 210).

performer. Figure 3 contains graphs for each of the 24 countries listed in the table (the top 20 and 4 special listings). For each country, both the benchmark and the actual are plotted from day 0 to day 225. The interested reader can peruse through the graphs - and note both the tight Gompertz fit, and the sharp divergences from forecast post day 150 for most countries. This is unlikely to be a global co-incidence – very likely, it is the effect of large increases in testing, as documented in Section 7.

**Table 6:Top 20 economies (plus 3) in COVID performance - until day 210 for each country**

| | | *Rank on Day of Infection* | | | | *Infections and Forecast on Day (in 000)* | | | |
|---|---|---|---|---|---|---|---|---|---|
| Rank | Country | 50 | 80 | 160 | 210 | Cases - day 50 | Forecasts - day 50 | Cases - day 210 | Forecasts - day 210 |
| 1 | Mexico | 46 | 12 | 2 | 1 | 11 | 11 | 758 | 823 |
| 2 | Ireland | 75 | 22 | 4 | 9 | 18 | 17 | 36 | 26 |
| 3 | China | 80 | 24 | 5 | 4 | 75 | 72 | 87 | 82 |
| 4 | Finland | 57 | 29 | 6 | 6 | 4 | 4 | 10 | 7 |
| 5 | Ghana | 85 | 8 | 10 | 2 | 3 | 3 | 47 | 51 |
| 6 | France | 16 | 16 | 11 | 24 | 33 | 34 | 300 | 154 |
| 7 | Japan | 113 | 39 | 1 | 35 | 1 | 0 | 64 | 24 |
| 8 | Netherlands | 64 | 15 | 13 | 28 | 33 | 32 | 109 | 50 |
| 9 | Thailand | 94 | 23 | 8 | 5 | 0 | 0 | 3 | 3 |
| 10 | Belgium | 72 | 25 | 21 | 23 | 42 | 41 | 116 | 61 |
| 11 | Switzerland | 47 | 28 | 17 | 18 | 27 | 27 | 51 | 30 |
| 12 | New Zealand | 60 | 32 | 15 | 7 | 1 | 1 | 2 | 1 |
| 13 | Germany | 81 | 27 | 18 | 12 | 29 | 28 | 242 | 167 |
| 14 | Malaysia | 61 | 18 | 23 | 8 | 2 | 2 | 9 | 7 |
| 15 | Denmark | 37 | 30 | 20 | 29 | 8 | 8 | 27 | 12 |
| 16 | Nigeria | 86 | 6 | 31 | 16 | 4 | 4 | 61 | 38 |
| 17 | Norway | 38 | 38 | 16 | 17 | 7 | 7 | 13 | 8 |
| 18 | Mali | 6 | 44 | 22 | 14 | 1 | 1 | 3 | 2 |
| 19 | Korea | 10 | 43 | 26 | 22 | 9 | 9 | 19 | 10 |
| 20 | Singapore | 116 | 4 | 25 | 15 | 0 | 0 | 56 | 35 |
| 21 | Italy | 31 | 49 | 19 | 11 | 148 | 149 | 293 | 205 |
| 31 | UK | 19 | 52 | 33 | 21 | 38 | 39 | 353 | 192 |
| 34 | Sweden | 52 | 33 | 40 | 25 | 14 | 14 | 91 | 44 |

*Note: Rank is a Borda rank of performance for day 60 through day 210 in increments of 10 days (see text for details)*
*Forecasts are based on Gompertz curves estimated for each country on basis of data until the 50th day of Covid cases being >=10*

Two facts deserve special mention. First, we really don't know why some countries perform well and others do not. For example, alone in the sub-continent is the stand-out performance of Sri Lanka – only 5811 cases, and less than 15 deaths. For primarily this reason (unknown initial conditions) we have concentrated on the delta – the change, as actually happened relative to the forecast. That is what the performance model does – but, obviously, the method has limitations .

*Sweden vs. Denmark*

For all discussions on COVID (including this paper), a discussion about two contrasting philosophies – Sweden and Denmark – is mandatory. Sweden alone has followed the herd-immunity model, a model which has consistently been followed in the US in all previous epidemics, including the large-scale flu epidemics of the late 1950s. In the beginning, day 50, Denmark and Sweden were ranked at 37 and 52, respectively. Both economies have improved their rank, but by day 210 Sweden was barely 4 notches in rank below Denmark – 29 vs. 25.

Since day 210 , the performance of Sweden has further improved. The rate of growth in cases in Sweden between these two dates was 25 %, the fourth lowest in the Advanced economies (the lowest three are Australia (6 %), and Germany and USA tied at 19 %). Denmark shows an increase of 60 %! The ranks on day 240 (with only 42 countries data) are Sweden 12 and Denmark 19. If a new benchmark base is chosen, herd-immunity Sweden might just be among the better performing economies (except China which has experienced the crisis the most (in number of days)) but which also is almost unique in controlling the virus to the degree it has.

*Aggregate Country Performance – A preliminary look*

More than two-thirds of the countries perform well at the time of the lockdown (Table 7); this is 110 out of 143 countries with the performance index less than 10 i.e. Cases were no more than 10 % higher than forecast. Even a month later (day 80), forty percent of the countries are have a performance index less than 10 %. A strict look at whether the curve was flattened is obtained by looking at column 3 - performance index less than 0 i.e. cases less than the benchmark. The number of countries achieving this goal drops to 33 on day 80. By end-July (approximately day 160 for most countries outside of sub-Saharan Africa, the good performers were down to only three countries (Hong Kong, Japan and Mexico). The number of countries which subscribed to the Hippocratic oath of doing no harm (index less than 10 on day 160) is 11 % or 7.7 % of the countries. This number drops to only 4 countries on day 210.

*Regional Performance*

Tables 8a and 8b report on performance indices for the different regions – for days 50, 80, 110, 160 and 210 (Table 8b presents the ratio of Actual to Forecast estimates as reported in Table 8a).

Note that our "primary" analysis ends on July 31st for most economies, and hence the late August thru October surge is *not* part of the "primary" test of whether lockdowns flattened the curve. We thus have the predictions from the benchmark equation, and the actual, change in cases.

**Table 7 - Performance of Country Models**

| Post - Intervention # days | As good as forecast or better | Better than forecast - Lockdown Worked |
|---|---|---|
| (1) | (2) | (3) |
| | *Number of Countries* | |
| 50 | 110 | 61 |
| 80 | 59 | 33 |
| 110 | 35 | 11 |
| 140 | 18 | 8 |
| 160 | 11 | 3 |
| 180 | 8 | 1 |
| 210 | 4 | 3 |

*Notes: Column 1 is number of days from day 1 (Cases >=10); column 2 is number of counties with performance only 10 % off (actual cases greater than benchmark); column 3 is index<=0 i.e. actual infections lower than predicted;* ***total country models - 143***

**Table 8a :COVID Infections and Benchmark Estimates from Country Specific Gompertz Models**

| | COVID Infections on Day | | | | Benchmark Infections on Day | | | |
|---|---|---|---|---|---|---|---|---|
| Region | *50* | *80* | *160* | *210* | *50* | *80* | *160* | *210* |
| Advanced | 476 | 1029 | 1459 | 2031 | 476 | 959 | 1088 | 1090 |
| East Asia | 103 | 145 | 448 | 849 | 100 | 136 | 173 | 174 |
| Europe-East | 97 | 190 | 743 | 1281 | 97 | 164 | 203 | 206 |
| Latin America | 103 | 439 | 2851 | 4766 | 105 | 305 | 949 | 1236 |
| MENA | 247 | 439 | 1487 | 2401 | 247 | 424 | 623 | 660 |
| South Asia | 28 | 137 | 630 | 746 | 27 | 77 | 232 | 283 |
| Sub-Saharan Africa | 30 | 77 | 324 | 389 | 25 | 50 | 106 | 116 |
| World | 157 | 527 | 1072 | 1738 | 156 | 377 | 488 | 558 |

*Notes: All data in 000; Large economies (USA, Spain, Russia, Brazil, India and South Africa Excluded)*
*Day measures the infection day with day 1 when infections were >=10*

Table 8a reports, on a regional basis, the actual number of cases, and the benchmark predictions after exclusion of the large population economies of USA, Russia, Brazil, India, and sub-Saharan Africa. In addition, Spain is excluded from regional estimates because of the complete breakdown post end July (until then, Spain was one of the best performing countries!).

Notwithstanding this fact, all regions show a sharp decline in performance the further the distance from day 50. This is an important result of this exercise, and contrary to most expectations and forecasts.

Several strong results emerge. First, it is encouraging to note how close the predictions are to the reality on day 50. This is broadly in-sample and broadly around the time of lockdown for most economies. All the regions (models estimated on a per country basis) are within -2 and 20 percent of the model, with the aggregate number of cases at 101 % on benchmark day. It has been argued by many, and correctly so, that the lockdown effect should be assessed after three to four weeks of implementation. Unfortunately for the lockdown advocates, by day 80, the aggregate count is 40 % higher than the benchmark.

**Table 8b: Matching Benchmark with Reality**

| | Ratio of COVID to Benchmark on Day (in %) | | | |
|---|---|---|---|---|
| | *50* | *80* | *160* | *210* |
| Region | | | | |
| Advanced Economies | 100 | 107 | 134 | 186 |
| East Asia | 103 | 107 | 259 | 488 |
| Europe-East | 100 | 116 | 366 | 622 |
| Latin America | 98 | 144 | 300 | 386 |
| MENA | 100 | 104 | 239 | 364 |
| South Asia | 104 | 178 | 272 | 264 |
| Sub-Saharan Africa | 120 | 154 | 306 | 335 |
| | | | | |
| World | 101 | 140 | 220 | 311 |

*Notes: All data in 000; Large economies (USA, Spain, Russia, Brazil, India and South Africa Excluded)*
*Day measures the infection day with day 1 when infections were >=10*
Estimates based on data reported in Table 8a

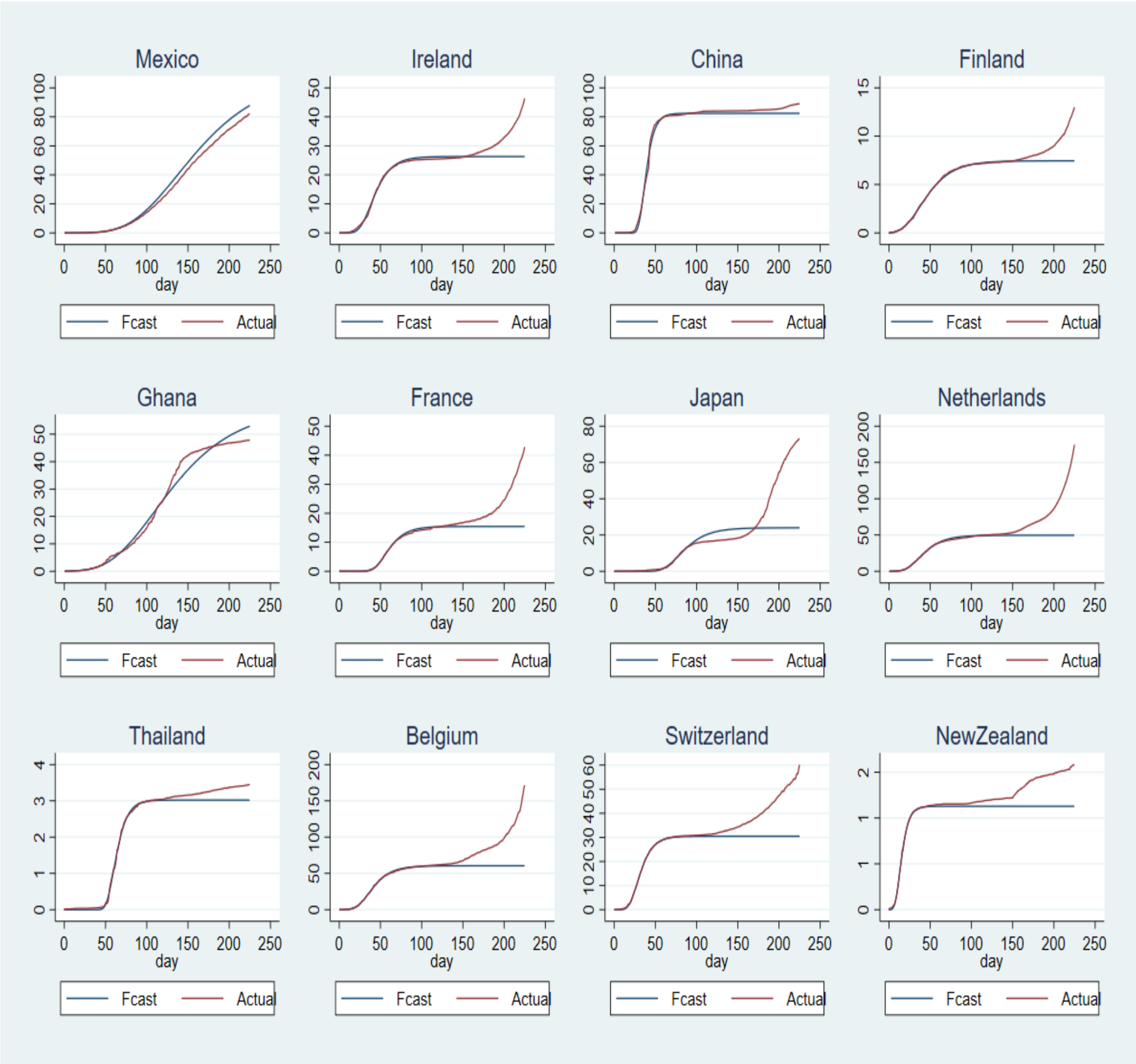
By day 160,  divergences from the benchmark (no intervention) forecasts are high for all the regions (and Region 1 will be like the others if either USA or Spain was to be included). By day 210 even the Advanced economies – with the best information and the most advanced health-care systems in the world – reality is almost double the amount forecast. South Asia (excluding India) has a performance index at 264 i.e. actual Covid count was 2.6 times the baseline count. Latin America, excluding Brazil, was worse in lockdown performance, but better than East Asia where lockdowns resulted in cases being 4 times the benchmark. Eastern Europe, even after excluding Russia, is the most divergent at 622 i.e. actual count of Covid cases were more than six times higher.

In summary, the relatively best-performing region with respect to the lockdown policy is the Advanced Economies region, a result also found by Bonardi et. al. (2020). East Asia (the region with virus stand-out economies like China, Cambodia, Laos, Viet-Nam), along with Eastern Europe, is tied for last place in the performance indices. East Asia is “let-down” by Indonesia and Philippines, two good performers in the first few months of the pandemic.

It is well understood, and recognized by all, that lockdowns inflicted considerable harm to the economy, jobs, and livelihoods of the bottom three-fourths of the population. Regardless of this recognition and ex-ante forecast of decision makers and epidemiological experts, and WHO, the world undertook this unprecedented step that lockdowns will save the hospital system from over-crowding and save lives.

**Figure 3 – Reality meets Benchmark – Top 20 plus economies**

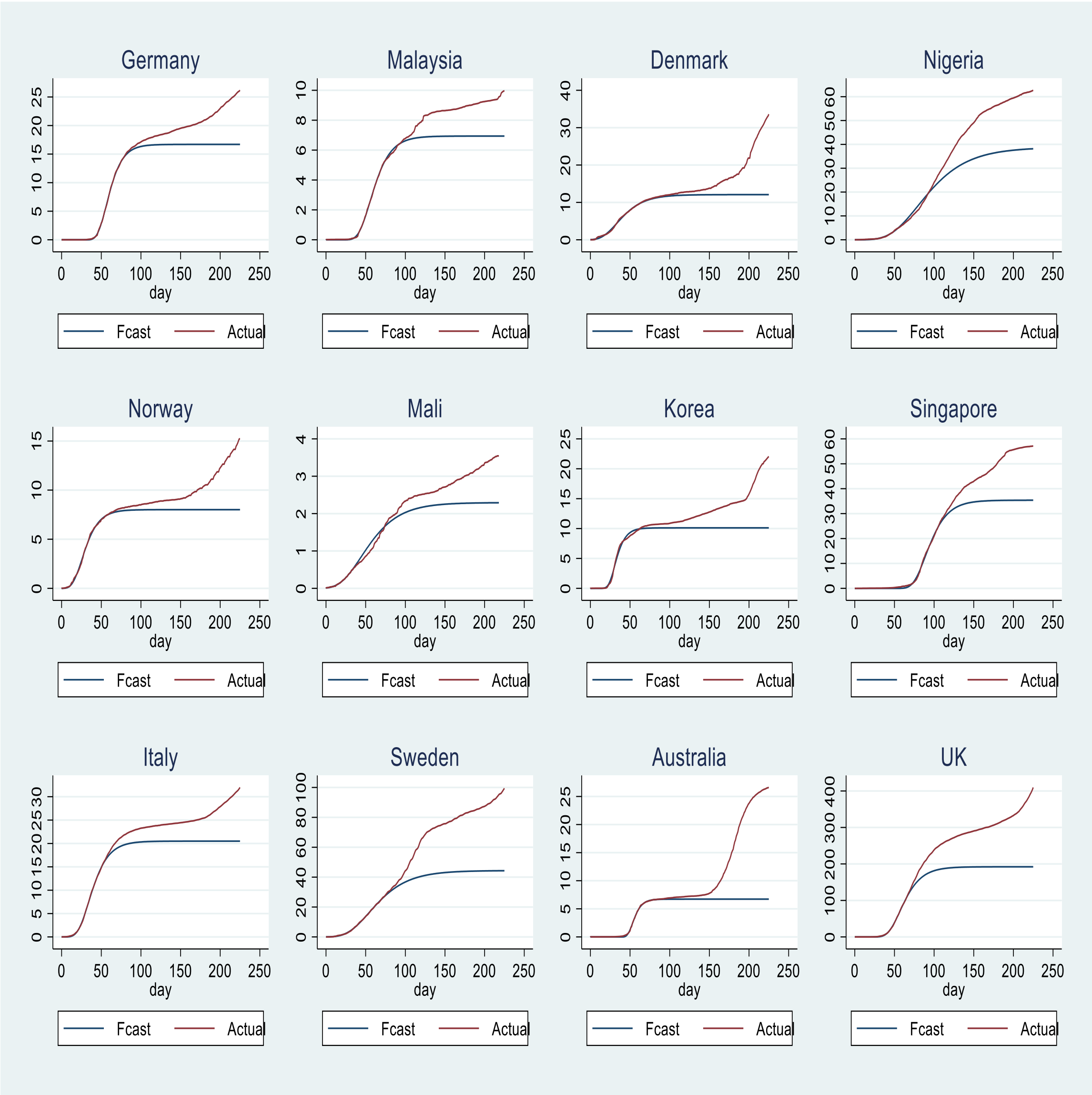
**(*Cases vs Forecast*)**




Notes: The *Fcast* (blue line) represents the forecast (benchmark) of infections estimated from data till day 50 for most countries (or until day 65 or day 80) for the rest. The estimation shifts to day 65 or day 80 if the Gompertz model does not converge and/or gives very unstable results. See text for details. **Actual** represents the cases as observed. Both Actual and Fcast (Y-Axis) is in 000 units; for some countries e.g. Mexico, France, Germany, UK) the unit is 0000. Note the out of sample accuracy for all countries until approximately day 150 which is 100 days post lockdown. As mentioned in the text, post day 150 cases (the second wave) was very likely affectd by increased testing and inclusion of asymptomatic cases. Day 1 is when cases crossed 10.

**Figure 3 – Reality meets Benchmark – Top 20 plus economies (contd).**

**(*Cases vs Forecast*)**




Notes: The *Fcast* (blue line) represents the forecast (benchmark) of infections estimated from data till day 50 for most countries (or until day 65 or day 80) for the rest. The estimation shifts to day 65 or day 80 if the Gompertz model does not converge and/or gives very unstable results. See text for details. **Actual** represents the cases as observed. Both Actual and Fcast (Y-Axis) is in 000 units; for some countries e.g. Mexico, France, Germany, UK) the unit is 0000. Note the out of sample accuracy for all countries until approximately day 150 which is 100 days post lockdown. As mentioned in the text, post day 150 cases (the second wave) was very likely affectd by increased testing and inclusion of asymptomatic cases. Day 1 is when cases crossed 10.

**Section 7: Lockdowns did not work – Bad Implementation?**

There has been a strong second wave of infections (and an equally strong *decline* in Covid related deaths) in late October. One interpretation of the data is that countries reopened too early, and that this caused the second wave i.e. lockdowns reduce infections, and re-opening before its "time" raises infections. An alternative interpretation, and one consistent with the results reported in the previous sections, is that the new ballooning of cases has very little to do with the re-opening because very likely, in the first instance, closure had very little to do with the spread of the virus. This is not to negate the importance of a second wave; rather it is to deny that it is related to the pre-mature re-openings of economies. By contrast, increased and extensive testing does seem to provide a better explanation of this second wave.

The more you test, the more you will find - because of the reality of asymptomatic carriers. An asymptomatic carrier is unlikely to be registered as a Covid case in the normal course of counting. But with testing, she will be caught in the net.

Two sets of data support the "more you test, the more you will find" hypothesis. The first is the by now established result that sero-prevalence counts around the world are at least four times, and possibly ten times, the number of actual infections. (Sero-prevalence surveys use blood tests to identify individuals who have antibodies against COVID). The reason for this divergence is the large presence of asymptomatic cases; the advocacy of more tests is likely to result in a larger percent of the population being tested, and hence, more infections. What this also implies is that the infection death rate should also decline.

Table 9 documents the infections, deaths, and tests for the world broken up into five groups – the first million, the first 10 million (reached on April 2nd ), the second ten million (reached on Aug 10), the third 10 million reached on September 16th and the final ten million a month later on Oct. 18th. The first million resulted in an infection yield of 23; for each 100 people tested around the world, 23 "yielded" an infection. Since then, the infection yield has dropped by almost two-thirds, and very likely this was due to asymptomatic cases. Consistent with this result, and interpretation, is the fact that the death yield (death as a percent of tests) has collapsed from the initial 1.2 level to now one-sixth that level (2 deaths per 10000 individuals).

**Table 9 : Pattern from the 1st Million to the 40th Million (in mil)**

| | | | | Yield | | | |
|---|---|---|---|---|---|---|---|
| date | Infections | Deaths | Tests | deaths /infections | tests /infections | infections/test | deaths /test |
| | | | | (%) | | | |
| 2-Apr | 1.04 | 0.0534 | 4.55 | 5.13 | 4.4 | 23 | 1.2 |
| 28-Jun | 10.1 | 0.49 | 114 | 4.85 | 11.3 | 8.3 | 0.40 |
| 10-Aug | 20.1 | 0.731 | 220 | 3.64 | 10.9 | 9.4 | 0.23 |
| 16-Sep | 30 | 0.941 | 343 | 3.14 | 11.4 | 8.0 | 0.17 |
| 18-Oct | 40.1 | 1.114 | 436 | 2.78 | 10.9 | 10.9 | 0.19 |

*Timing and Intensity of NPIs*

We next turn to an analysis of an important set of conclusions reached by recent research (Dave et.al. and Amuendo-Dorantes et.al. for US, Amuendo-Dorantes et.al for Spain, and WEO for all 73 countries. This research reaches three conclusions – first, that lockdowns result in less cases, *ceteris paribus*, than no-lockdowns. We have offered several tests of this hypothesis and found little support; indeed, we find considerable negative support for this conclusion! The second conclusion is that NPI's adopted early in the virus cycle are more productive. And third that stricter lockdowns, and short-lived lockdowns are preferable to milder and longer lockdowns.

The model estimated by this research appears to be of the following general form:

$$yC = a + b_1*(t_L - t_1) + b_2*yS \qquad (6)$$

where yC is the (average) log growth in the number of cases from the day of the lockdown to the "terminal" date t (expected to be 30, 60, or 90 days); yS is rate of growth lockdown day and day t; $t_L$ is the calendar day the lockdown was implemented and $t_1$ is the calendar day of the first case.[21] The difference between ($t_L - t_1$) is meant to capture the "lateness is bad hypothesis".

Our results reject both elements of the "early lockdown is good, more stringency is better" hypothesis. Libya enforced a lockdown one day *before* the first case and has ended with more than 43000 cases (population only 6.7 million); nine days after the first case Peru imposed a lockdown and has ended with more than 850,000 cases (population 33 million); and China, probably the most successful lockdown-virus control nation (and no second-wave!), imposed a lockdown very late – day 37 if December 15 is taken as the day of the first case. Further, only 25 % of the countries imposed a lockdown *after* day 37. In other words, most, nearly all, countries imposed a lockdown much before China did – and performed considerably worse. The above heuristic evidence does not support the early lockdown conclusion.

A rigorous test of the early lockdown is successful strategy is reported in Table 10. We report straightforward Occam's Razor tests. The dependent variable is the log rate of growth of cases, from the date of the first case to 30, 60 and 90 days later. (We also experimented with the first case being when the 10$^{th}$ case, or the 27$^{th}$ case (to match the data from China) was recorded. The most relevant independent variable is the average growth in the Oxford stringency index from day of lockdown to the end date. This mimics the dependent variable in equation (6). The lateness variable, *LateI*, represents the number of days difference between the lockdown date and the day of the first case. In addition, we include the fraction of the population above age 80 as one control variable.

We report four regressions – one each for the growth rate in cases (1, 2 and 3 months after date of lockdown[22]). The fourth regression, and the one used for our added variable plots below, excludes three outlier observations – Lesotho, which implemented a

[21] We experimented with the day of the first case as the calendar day when the 10$^{th}$ case was observed, and to parallel the data from China, the day when the 27$^{th}$ case was observed (Wuhan on December 31$^{st}$.) All formulations yield the same result.

[22] The lockdown variable used is the full lockdown variable reported in ACAPS. Other definitions of lockdowns yield similar results.

lockdown 47 days before the first case; Puerto Rico (lockdown on day minus 12) and Angola (on day 5 after lockdown).

The results. Fraction of population >80 years does increase the growth rate of infections, but three months later, the effect is not significant. Rate of growth in stringency is always very significant and very positive. The elasticity is also very stable at around 1.4 i.e. each percent increase in stringency adds approximately 1.4 percent to the growth rate in cases. The lateness variable is only significant one month after the lockdown – and its effect is negative and counter to the conclusion reached by others – a later date of lockdown lowers the rate of growth of infections.

Figures 4a and 4b report the added variable plots after exclusion of three outliers.

**Table 10: Late and Less Stringent Lockdowns are better**

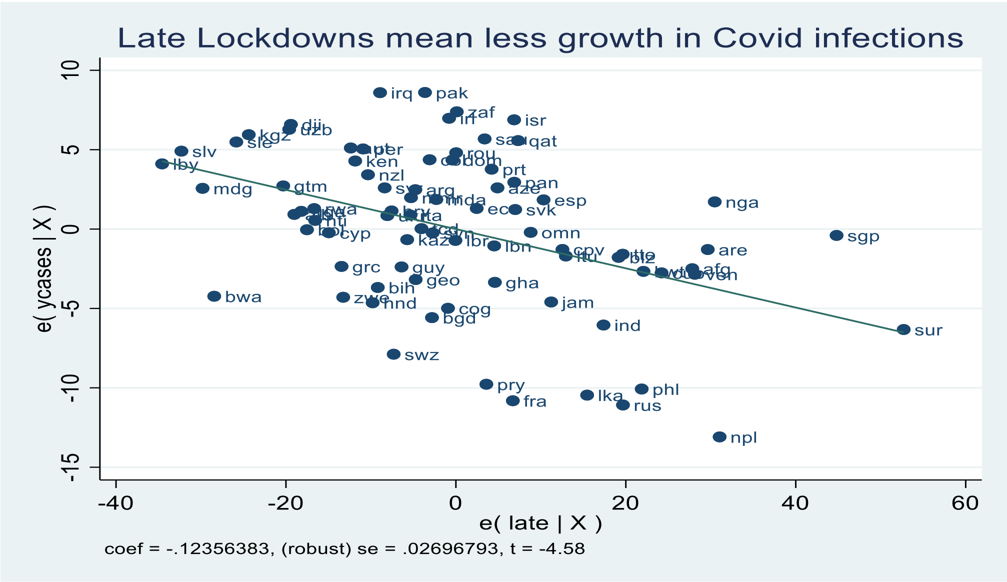
*Dependent variable is average rate of growth in Covid cases from first day to*

| | Months after first date | | | |
|---|---|---|---|---|
| | 1 | 1a | 2 | 3 |
| Average growth | 1.616*** | 1.428*** | 1.483*** | 1.375*** |
| in OxGRT stringency | (5.07) | (5.04) | (4.80) | (4.59) |
| % male population > 80 years | 3.186*** | 3.432*** | 1.747** | 0.509 |
| | (3.96) | (4.37) | (3.12) | (1.42) |
| How late lockdowns? | -0.0694* | -0.124*** | -0.0244 | -0.00536 |
| (Difference between lockdown day and first infection day) | (-2.07) | (-4.58) | (-1.42) | (-0.45) |
| _cons | 10.24*** | 12.51*** | 7.557*** | 6.501*** |
| | (6.72) | (10.78) | (11.92) | (15.85) |
| N | 81 | 78 | 81 | 81 |
| adj. R-sq | 0.4479 | 0.5272 | 0.3600 | 0.2285 |

t statistics in parentheses; * p<.05; ** p<.01; *** p<.001

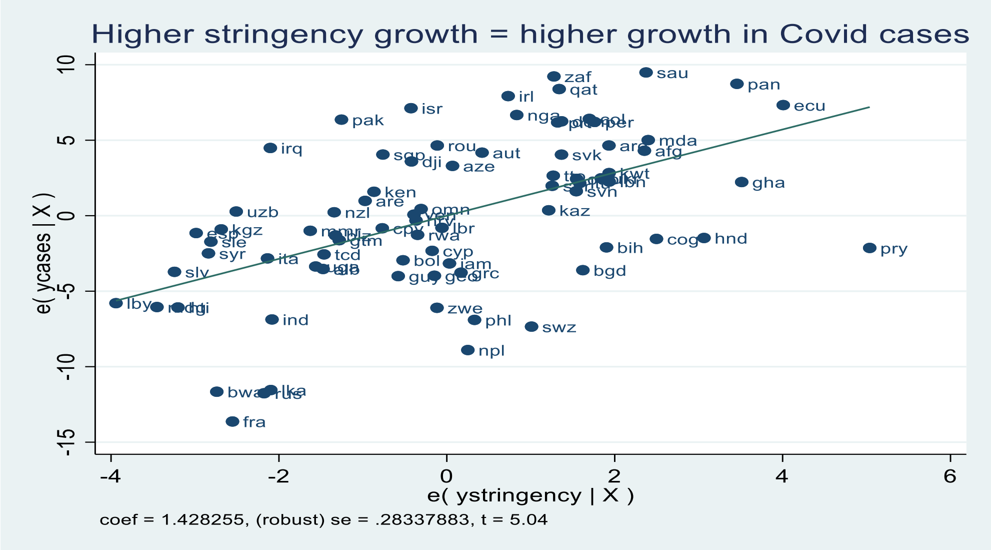
(*Regression 1a excludes three country observations Lesotho, Puerto Rico, and Angola and is the equation used in the added variable plots below).*

**Figure 4a: Late Lockdowns work better than early lockdowns**




Notes: Added variable plot for lateness of adoption where lateness is the difference in days between the date of lockdown and the date of the first case. Equation 1a Table 10.

**Figure 4b: Strong relationship between more stringency and more cases**




Notes: Added variable plot for the strength of stringency between the first day and the 30th day. .Equation 1a Table 10.

### *Lockdowns Are not Effective – What is to be done?*

Several tests of controls and COVID have been presented, and invariably, COVID wins, except in a handful of countries. It is important to identify why countries like China, Hong Kong, Taiwan, Sri Lanka, Mali, and Sri Lanka succeeded in controlling the virus. Korea, Japan, New Zealand, and Singapore all had good performance and low number of cases, and in many of the above countries (excluding China) the Covid case fatality rates are also very low. A lot to be learned from these economies. For the moment, what the above research shows is that a very large proportion of cases lockdowns just did not work. So what works? The herd-immunity model of Sweden obtains some support, but not enough to convince most countries suffering from lockdown fatigue, and lockdown failure.

Earlier, we had termed lockdowns as "unnatural" experiments. India's experience with lockdowns, and an alternative, is a genuine natural experiment. India, along with most countries, was guided by the advice of experts and the successful experience of Wuhan. The whole world thought they could replicate the China model, only to realize that that was just not possible.

India lifted the lockdown (imposed on March 21st) in stages and by the end of July, the reopening of the economy (or the closing of lockdown) was on track. With the re-opening, India launched a new non-lockdown policy of the 3-Ts – Testing, Tracing, and Treatment (via isolation). This 3-Ts strategy rests on a mechanism to identify districts with greater COVID cases and isolating them from the rest. Economic activity was permitted outside the containment zones/districts. It is likely that the new Indian Covid strategy is the one followed by the lockdown successful economies mentioned above. Importantly, Japan succeeded *without* a national lockdown.

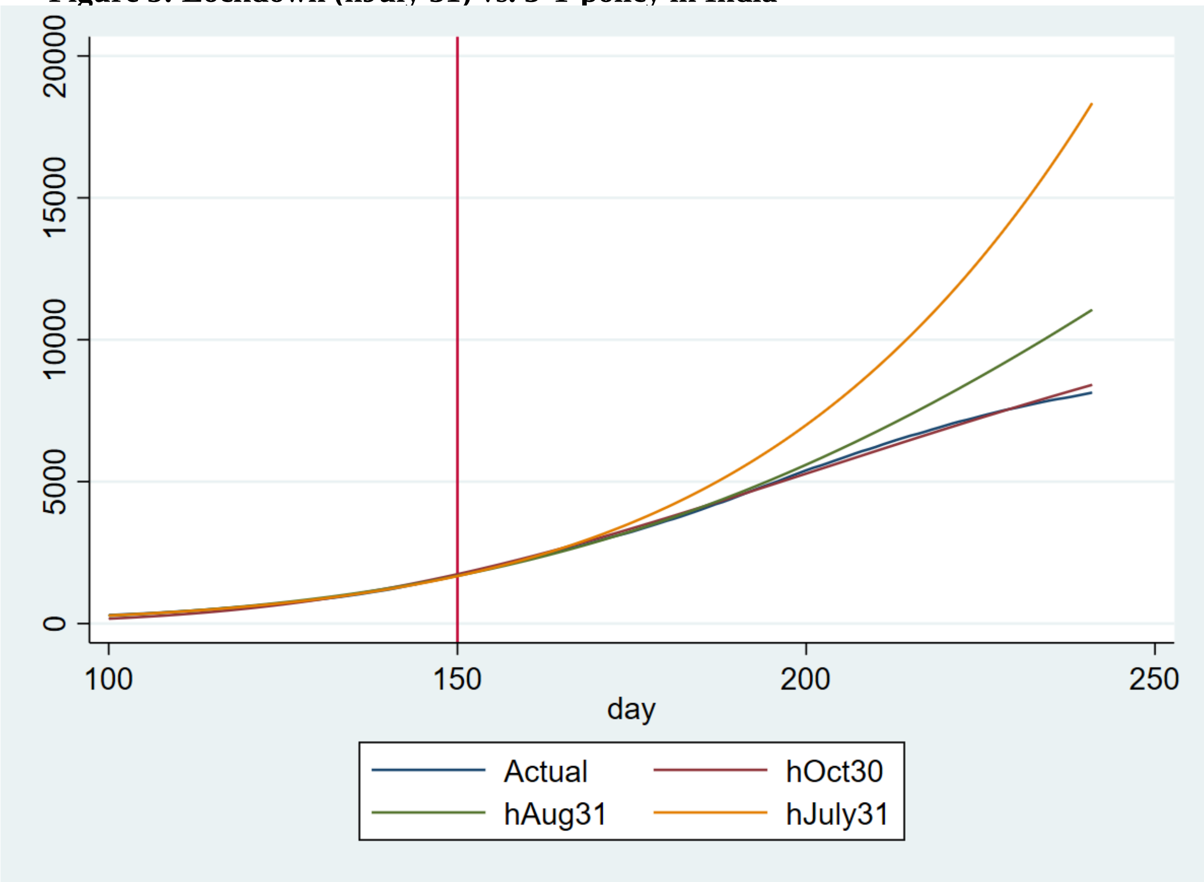
How well has this 3-T no lockdown policy worked? As European nations prepare to go thru another lockdown in attempting to combat a second wave (a lockdown with a different name is still a lockdown), it is worth studying the results, to date, of the Indian approach.

Figure 5 presents four Indian COVID lines – Cases (in 000) from the beginning of the virus (labelled Actual); a Gompertz model (estimated as of October 30, hOct30); and two other forecast models – one estimated as of July 31 (hJuly31) and one a month later (as of Aug 31st, hAug31). The results are (shockingly) revealing and provide a "live" example of the ineffectiveness, rather detrimental, nature of lockdowns and confirmation that policies like India's 3-Ts are worthy of emulation.

The red line in Figure 5 is day 150 for India (July 31st). On Oct. 30th, the original lockdown policy would have resulted in 18.3 million cases. One month later, estimate for Oct 30th was a reduction in COVID cases by approximately 7 million to a level of 11.1 million. Actual cases on Oct.30 – 8.1 million; forecast level of cases according to a model using all of the data to date – 8.4 million. An estimate of a logistic model yields an estimate of inflexion point as 193 i.e. according to the logistic model, approximately day 400 should be the end of the crisis, or about five months from now. The Gompertz model yields an estimate of 14.8 million cases as the final count of India, and occurring sometime near the end of March.

This section, however, is not about forecasts but rather about how the Gompertz model can help identify trends and the efficacy of non-lockdown policy. A simple application of the estimates suggests that the new policy has helped reduce infections to less than half of what would have been if India had continued with lockdowns.

**Figure 5: Lockdown (hJuly 31) vs. 3-T policy in India**




*Notes: The lockdown was in effect till July 31st (day 150 after the 10th case). The Y axis is the number of cases (000) and the X-axis is number of days of the virus once cases crossed 10. The line labelled hJuly31 is the model estimated till July 31 and out of sample afterwards; similarly for lines labelled Aug 31 and Oct 30. Note that there is a close fit between the Actual and forecast line for today (Oct 30); as well as a close fil between hJuly31 and Actual till approximately day 150. The distance between hJuly31 (and hAug31) and the Actual line is how many less cases are present today because of a departure from lockdowns to a 3-T policy.*

**Section 8: Conclusions**

As the pandemic has raged on, so has research on non-pharmaceutical interventions to stem its spread. For the first time in human history, lockdowns were used as a strategy to counter the virus. While conventional wisdom, to date, has been that lockdowns were successful (ranging from mild to spectacular) we find not one piece of evidence supporting this claim. This paper has attempted to document, and estimate, all the methods employed in the literature. Broadly, the evidence is as follows:

China was the origin of the virus, and the origin of the lockdown works hypothesis. It is true that the low numbers of virus in China (controlling for size of the population) are indicative of spectacular success. Yet, regional and other comparative data for China does not support the hypothesis that *lockdown* was responsible for the low rate of infections. Research is needed to identify why countries as diverse as China, Sri Lanka, Taiwan, Sudan, Laos, Vietnam etc. succeeded while many other countries, with identical characteristics, and identical policies, failed.

Lockdowns were never practiced before despite several provocations. We presented evidence how the US explicitly downgraded the possibility of lockdowns despite severe influenza crises (with the same estimate of excess deaths as COVID) in the late fifties and early sixties. Why the world chose to inflict lockdowns on itself in 2020 is a question left unanswered by most, including our, research.

There has been a surge in COVID infections (but not deaths) in most parts of the world in the last three months. We show that this surge is most likely, and dominantly, related to increased testing. Infections as a ratio of tests has been averaging less than 1 in 10 over the last several months; this ratio is near identical to the results of serological surveys. These surveys show that actual infections are more than 10 times the recorded infections suggesting that the inclusion of asymptomatic cases (not in the count before the advent of extensive testing) in recorded infections is a large part of the second wave.

The evidence suggests that the conclusion that the second-wave infections are due to pre-mature reopening of economies maybe in error. Two important reasons of why the conclusion is not supported by the evidence. First, if re-opening has caused the second wave, then it must be the case that closing resulted in less infections. We have offered a wide variety of evidence that emphatically rejects the lockdown equals less infections hypothesis. Over 20 indicators of lockdown were tested to identify their effects on the rate of growth of infections (or deaths). In less than ten percent of the cases, the lockdowns had a positive effect. In more than three times the “positive” cases, the effect was perverse i.e. lockdowns led to more infections, more deaths.

As we have stressed throughout, a direct test of lockdowns on cases is the most appropriate test. This direct test is a before after test i.e. a comparison of what happened post lockdown versus what would have happened. Only for 15 out of 147 economies the lockdown “worked” in making infections lower; for more than a hundred countries, post lockdown estimate of infections was more than three times higher than the counter-factual. This is not evidence of success – rather it is evidence of monumental failure of lockdown policy.

Lately, some have argued that it wasn’t lockdown policy to blame for failure but rather an inappropriate or incorrect application. This interpretation is in error on at least two counts. First, given that the lockdown was unprecedented, and explicitly rejected as a policy before, there is no historical precedent basis to assume that lockdowns work. Second, we conduct several direct tests of lateness of lockdowns on the rate of growth of cases (and deaths). We find, and present, evidence to show that contrary to assertions of others, lateness of lockdowns led to less, not more, infections. Another indicator offered is that the lockdown policy failed because the lockdowns were not stringent (via the OxGRT stringency index) enough. We find, systematically, a rejection of the “high stringency is good” hypothesis i.e. we find that the greater the stringency, the higher the rate of growth of infections.

In conclusion, we find overwhelming evidence that lockdowns were a failure. Unfortunately, we are not able to provide evidence of what did work in controlling infections. One inference from our results is that the Swedish policy of developing herd-immunity is the one most likely to be successful. This was the policy for success in previous pandemics. A reality vs. counterfactuals comparison of Sweden and Denmark shows that Sweden did significantly better than its lockdown neighbor. Over a three month post lockdown period, Sweden's performance ratio was 75 i.e. actual cases were a third higher than forecast by a counter-factual model. In the case of Denmark, the performance ratio was 44.5 i.e. actual cases were more than twice (100 divided by 44.5) the forecast of a counter-factual model.

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