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Lessons from Disease and Economic Surveillance during COVID in India§

ABSTRACT This paper describes disease and economic surveillance during COVID, along with the uses of that surveillance, and lessons learned about the pandemic from that surveillance. It ends with policy suggestions on how to gather intelligence during the next pandemic in India and how surveillance informs suppression policy. The important themes that I stress are the value of population-level surveillance, understanding the incentives and disincentives for surveillance and reporting, and tailoring policy to the results of surveillance.

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JEL Classification: *I10, I14, I15, D82, D83*

1. Introduction

Chinmay Tumbe, in his book *The Age of Pandemics*, argues that India has historically been hit harder than other countries by pandemics (Tumbe 2020). For example, India lost more lives to each of cholera, the plague, and the 1918 flu than other nations.

COVID may provide additional evidence for his hypothesis. Officially, India has 34 million cases and 500,000 deaths. The actual cases and deaths are likely much higher. Serology suggests that 90 percent have antibodies, though some of that is due to vaccination. Estimates of excess deaths suggest that 5 million or more may have died. The economy also took a hit. Poverty spiked during the pandemic and remained elevated after the national lockdown.

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Are there lessons we can learn from India's experience during COVID that might help the country better handle the next epidemic, whether it is Monkeypox or pandemic flu? In this paper, I review India's response to the pandemic, discuss several efforts to track the spread and consequences of the pandemic, and explore implications for how to handle pandemics.

The paper has four substantive parts, corresponding to stages of the epidemic and India's policy response: before the pandemic reached India, just before the lockdown, during the lockdown, and after the lockdown. (I stop before vaccination as the paper is already quite long.) In each section, I discuss surveillance strategy and associated policy response. Each of my discussions tries to answer four questions: What did the government do? Why did it do so? What were the consequences? and What should the government have done differently?

There are a few broad lessons and reforms that I highlight. First, policy should consider both individuals' and governments' (imperfect) incentives to test for infection, to report test results, and to act to stop infection. Likewise, the government should keep an eye out for unintended consequences of policies like quarantine. Second, the government should build a disease and economic surveillance infrastructure and commit to regular reporting, even before a pandemic. When doing so, it must take sampling seriously, not make strong assumptions about the nature or course of disease, stock necessary supplies and expertise, eliminate obstacles to testing, and learn how to interpret different types of tests. Third, the government should think carefully about institutional design and ensure that agencies are neither overwhelmed nor have conflicting incentives. Fourth, the government should connect disease surveillance to economic data so as to facilitate interpretation of the latter. Likewise, it should ensure that policy is updated based on disease and economic surveillance, otherwise, surveillance has less value and policy can go awry.

Before proceeding, let me issue a caveat. I will often criticize the government for having done this or that. However, the Indian government is not a unified entity. There are battles between the executive (say, the office of the Prime Minister or a Chief Minister) and bureaucratic agencies, as well as between agencies and between the Centre and States. When some arm X makes a decision, perhaps in error, there will be some other agency or political actor that will attempt to change or redress that decision. Moreover, the Indian Government is not at all unique for not handling the pandemic perfectly. Similar criticisms can be heard of governments around the world, including those of the US, UK, Sweden, China, and Australia. This is not to excuse bad decisions, but to suggest that the COVID pandemic is a teachable moment for all countries. The goal should not be to cast blame but to make changes and better prepare for the next pandemic.

2. The Pandemic Reaches India

COVID officially reached India in late January, ostensibly in Kerala (Andrews et al. 2020). Whether these were the first cases, we will likely never know. We did not immediately have a large number of tests for COVID, and, in any case, they were not immediately deployed to screen all or a random sample of travelers.

How could India have detected COVID earlier and would that have made a difference in its response? India's best early warning system is other countries' reporting of outbreaks: this provides signals of a threat before it reaches India's boundaries.

2.1. Foreign Surveillance

The problem with foreign surveillance is that each country has little incentive to reveal a pandemic within its boundary (Malani and Laxminarayan 2011; Laxminarayan et al. 2014). Doing so triggers travel and trade restrictions.[1] The WHO tries to change incentives by providing medical expertise and resources. But this benefit has little value for countries that already have great health care capacity. It is not surprising then that China may have delayed the announcement of COVID (Watt 2020) and did not fully cooperate with WHO efforts to identify the origin of the virus. Unless an outbreak originates in a country that has automated surveillance that the government has no discretion to censor or in a country that needs and values WHO assistance, relying on foreign surveillance is unlikely to be effective.

Even if disease testing is conducted by the WHO, one should not expect perfect reporting of outbreaks. This is not because of technical limits of testing, but incentives. Surveillance by the WHO depends on countries allowing the organization into their country. If the WHO's tracking was too sensitive, then countries at high risk of disease outbreaks would not permit WHO testing. Doing so would be equivalent to always disclosing outbreaks immediately. As we noted above, sometimes the costs of sanctions are greater than either the medical support from the WHO or the country's altruistic desire to help the world community. The WHO is surely aware of this. So, it rationally has to tolerate a country's efforts to delay or suppress information on outbreaks to ensure that it at least obtains some information on that outbreak. The alternative might be even less information on outbreaks.

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1. A related problem I encountered later in the pandemic and within India is that governments may not want to test if the results from testing will force it to adopt a policy that it does not prefer. Officials from a State that I will not name informed me that the State was not eager to test for COVID because doing so would reveal a high level of cases that, in turn, would cause the press to demand a lockdown. Politicians, whose supporters cared not just about population health but economic output, did not want a lockdown. But the politicians predicted that they would not be able to resist press calls for a lockdown without paying a very high electoral cost.

The last two paragraphs contain bold—and politically volatile—claims. But they reflect both the logic of economics and diplomacy. Imperfect incentives for testing are a reality, and we will also see this play out domestically, with testing efforts within countries, including India. An important challenge for pandemic policy is to create incentives for testing and reporting outbreaks. But until that is accomplished, India should not rely on early warning of outbreaks by foreign countries.

2.2. Response to Early Warning

Although the world may have received delayed signals of the COVID outbreak, it did receive those signals. Did countries act immediately when they ultimately received evidence of outbreaks? For the most part, no. For example, India did not act until cases reached its shores.

This delay is unsurprising, and behavior that was not unique to that country. Indeed, tardy response to threats is both rational and should be expected in the future. A country receives many warnings about potential disease and non-disease risks (such as climate change, economic threats, and security threats). However, the country has limited resources and cannot act decisively on each risk. Moreover, some risks turn out not to be serious. It must choose amongst threats based on some assessment of their expected harm.

Many people will argue that governments were warned about COVID. Famously, Bill Gates had been warning of the risk of a pandemic for years. But that is true about nearly every major calamity and—importantly—many non-calamities. How do governments determine which threats are worth acting on, and which are not? Ex-post evaluation after a disaster is unhelpful because it provides an incomplete picture. India did not act early on COVID, and in hindsight that was a mistake. But India also did not act early on SARS, and in hindsight that was not a mistake.

Experience with prior crises suggests that countries use actual harm as a way to distinguish between credible and non-credible threats, between threats to which they will and will not respond (Malani 2009). We have seen this over and over, with the Asian Tsunami, the 2008 financial crisis, Mumbai terrorist attacks, and now COVID. The result is that governments (rationally) fail to take preventative action and appear to be caught flat-footed.

The implication is that we should expect the same next time around. Early warning of a pandemic is insufficient to trigger a response. Surveillance will reveal many risks, but not all will be credible risks, until they reach India's shores. Therefore, surveillance is a necessary, but not sufficient condition for early action. However, it will prove useful once a threat has arrived and the government is compelled to act. Specifically, it will help the government gauge the significance of the threat and the efficacy of its response. In addition, it will assist individuals, who may be more risk-averse or credulous than the government, to take private actions to protect themselves.

2.3. Travel Restrictions

Background. The Central Government's initial response to the pandemic consisted of a series of travel restrictions. India was not unique in responding this way: most countries did. The government restricted travel to India from high-risk countries, and then from all countries. It later restricted travel across States.

Travel restrictions are one stop along a continuum of movement restrictions. Movement restrictions have three components: Who, what, and where. Who governs the class of people governed by a restriction? What governs the extent of the restriction: what movement is restricted? 'Where' tells us the span of the restriction: what is the area over which it applies?

Travel restrictions cover a large area: a country or state. The restriction applies to all persons; however, there is a period of adjustment wherein residents and foreigners are eventually allowed to enter and leave, respectively. Finally, travel restrictions typically only restrict entry and exit from jurisdictions such as the country or state.

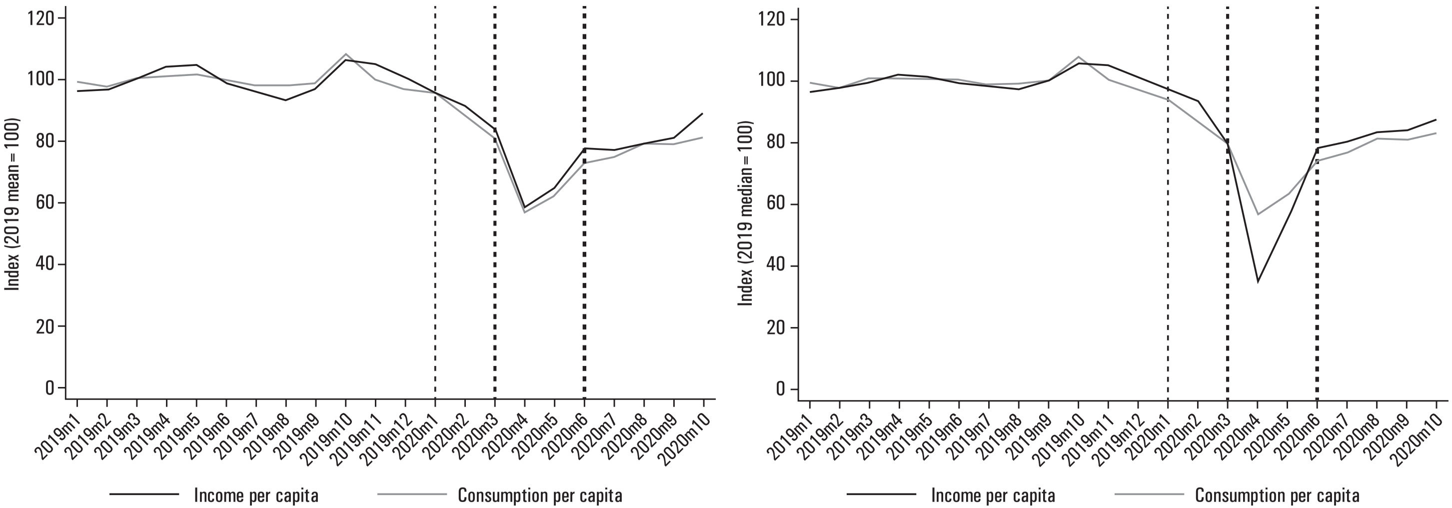
In contrast, lockdowns, containment zones, and quarantines have a bigger "what": they more sharply restrict movement within an area, for example, limiting the reasons for which a person can leave their home. The difference between lockdowns, containment zones, and quarantines is in their "where": lockdowns apply to a larger area (say, a whole district or larger area) than containment zones, which apply to a larger area (say, one or more city blocks) than quarantines (which apply to a home or even a room in a home). India used these measures once the pandemic reached its shores, and I shall discuss their efficacy below.

Implications. Casual—rather than causal—analysis suggests that travel restrictions—India's initial response—are unlikely to be very cost-effective, that is, their benefit in terms of delaying the spread of infection is smaller than the extent to which they harm the economy.

Travel restrictions are of limited value in controlling epidemics. Empirically, they did not prevent the infection from reaching any non-island country. India has limited State capacity to keep people out. Politically it is difficult to lock citizens out because they have connections and thus advocates at home. Moreover, travel restrictions are a blunt tool. They do not discriminate between safe and unsafe travelers, especially at the beginning of a pandemic when testing is scarce.

At the same time, economic surveillance during the pandemic suggests that travel restrictions may have substantially impacted incomes (Figure 1). Data from the Consumer Pyramids Household Survey suggests that mean and median incomes fell even before the national lockdown in March 2020 (Gupta et al. 2021b).

FIGURE 1. Time-series of Mean and Median Income and Consumption and Poverty, 2019–20



Source and Note: Figure and notes copied from Figure 2 in Gupta et al. 2021b. The figure was constructed by first dividing the household income by the household size to calculate per capita income, then dividing by the State x urban status specific mean or median 2019 income, and finally calculating monthly means or medians using individual member weights. A similar process was followed for consumption. Dashed vertical lines in January 2020, March 2020, and June 2020 indicate the month of first case (left vertical line), the month the national lockdown started (middle vertical line), and the month the national lockdown ended (right vertical line). All values are inflation-adjusted in 2012 INR.

Perhaps there were collateral benefits of travel restrictions. They signaled to Indians two things. First, the government was on the case. That sort of reassurance may be important for maintaining allegiance. Second, it may have signaled to people that worse restrictions may come, and they had better begin to adapt. I suspect this is the reason that there was a surge in migration out of cities even before the surprise announcement of the national lockdown.

Be that as it may, going forward one should be aware that travel restrictions are an incomplete solution. At best they reassure the public and buy time for a more thoughtful response.

3. Early Surveillance within India

3.1. Symptomatic Surveillance

Background. Initially, surveillance for COVID took place in hospitals, focused on symptomatic individuals, and looked for viral fragments in sampled sputum. This strategy was not uncommon around the world.

Testing of symptomatic individuals in hospitals reflected a medical doctor's mindset. A medical doctor conducts diagnostic testing on patients that come to her with some indication that testing is warranted. She does not test seemingly healthy individuals in the community. That strategy makes sense for non-communicable diseases. A demand-pull strategy respects a need both to allocate scarce resources and for patient consent. But it is inappropriate for communicable diseases, especially when asymptomatic transmission is possible. Externalities from illness may warrant a supply-push strategy where the government conducts testing to assess the extent of risk from infected (though perhaps asymptomatic) individuals to uninfected individuals.

Implications. Initial focus on symptomatic cases in hospitals meant that surveillance missed asymptomatic cases in the community (Thacker 2020). In hindsight, we know that perhaps 90 percent of infections were asymptomatic, even early in the pandemic (Kumar et al. 2021). As a result, either the government had incomplete information, or the government did not prepare the population for the coming storm. If the government did not know the extent of community spread, it may have led it to both under- and over-reacting to the pandemic. At the start, it did not warn individuals to self-protect. Then, the government, perhaps due to alarmist forecasts from disease modelers, did a 180-degree turn and implemented one of the harshest lockdowns the world had seen.

Bihar conducted a study in spring 2020 that suggested a potentially large gap between surveillance at hospitals and surveillance in the community. Specifically, the State randomly sampled people from trains with migrants returning to Bihar from States across the nation after India's national lockdown was lifted in May and June 2020. Table 1 reports the infection rates reported in

TABLE 1. Difference between Positive Test Rates among Returning Workers and among Residents of State, by State or Territory of Origin and Time Period in 2020 (Percent)

State	*(1) May 4-May 21*		*(2) May 22-May 31*		*(3) June 1-June 10*	
	State-Reported Positive Rate	*Difference*	*State-Reported Positive Rate*	*Difference*	*State-Reported Positive Rate*	*Difference*
Andhra Pradesh	0.5	0.6*	0.6	5.3***	0.9	2.2***
Chandigarh	6.7	3.9**	5.9	2.3	4.7	0.7
Chhattisgarh	0.3	3.5***	1.5	2.5	3.0	3.0
Delhi	7.5	5.8***	14.3	1.8**	24.6	11.8***
Gujarat	8.7	3.0***	8.9	0.0	8.6	0.5
Haryana	1.0	6.0***	3.8	7.0***	8.4	3.7***
Jammu & Kashmir	0.9	6.8***	1.7	2.8	2.9	3.4
Jharkhand	0.7	0.5	1.3	2.9***	2.9	3.4**
Karnataka	1.0	0.7*	1.4	6.1***	2.5	2.1***
Madhya Pradesh	4.1	0.9	5.0	0.7	3.2	0.1
Maharashtra	17.4	7.8***	18.1	0.0	18.8	9.5***
Odisha	1.4	0.7	2.0	0.8	3.9	3.9**
Punjab	2.6	0.5	0.9	3.9***	0.9	4.0***
Rajasthan	2.2	0.9**	1.9	3.1***	2.1	2.7***
Tamil Nadu	5.0	0.5	7.1	0.2	9.8	6.1***
Telangana	-	-	-	-	-	-
Uttar Pradesh	2.5	1.6***	3.1	11.4***	3.0	7.1***
Uttarakhand	0.8	0.8	5.2	0.0	6.9	4.9
West Bengal	2.2	4.6***	2.6	1.7*	4.2	0.4
Total	4.5	1.8***	5.5	5.6***	6.4	2.4***

Source and Notes: Table and notes have been reprinted from Table 3 in Malani et al. (2020a). Statistics for States from which testing results are not available are marked as missing. For some States, the dates for the test result data do not correspond exactly to the dates of each of the three periods; in those cases, we take data for the closest period corresponding to each of the three periods. The State-reported positive rate is the number of confirmed cases reported by a State divided by the number of tests conducted by that State during the relevant time period. Asterisks (*/**/***) are used to mark statistical significance (at the 10/5/1 percent level).

each State during three periods and shows the degree to which the State-reported rates fell below rates estimated with random testing on returning trains. The average under-estimate ranged from 1.8 to 5.6 percentage points. This implies that the actual rates of infection might be perhaps 40 to 100 percent higher than the official estimates. It is possible that migrants, who come from dense slums, have a higher rate of infection, a topic to which I will return later. It is unlikely, however, that Bihar's estimates reflect infection on crowded trains because infections caught on trains were unlikely to be detected upon arrival when testing was conducted.

Reforms. A better approach would have been to understand that infectious diseases are better handled as a public health rather than private health matter. That requires both testing symptomatic patients and testing a representative sample of the population. The latter would have revealed the extent of community spread. Community surveillance should also have been done repeatedly so the country could learn both the level of infection and its rate of spread.

Switching from a therapeutic to public health posture may require institutional reforms. In India, the National Centre for Disease Control (NCDC) resides in the Ministry of Health and Family Welfare (MoHFW), much as the CDC is technically part of the U.S. Department of Health and Human Services. However, at the start of the epidemic, the COVID war room was set up in the MoHFW and, instead of the NCDC, the Indian Council of Medical Research (ICMR), played the central surveillance role. That the war room was in the MoHFW is unsurprising: the scope of the epidemic required an entity that also managed the country's health care facilities and drug approval system. What was surprising was ICMR's displacement of NCDC in testing strategy as ICMR was mainly a research entity before the pandemic (Mookerji and Chitravanshi 2021). This research mindset may have slowed down testing as academic organizations tend to be conservative to preserve their scientific credibility. Yet what was required at the start of the pandemic was a bias for action, in this case, on testing. It is true that NCDC needed strengthening, both in terms of resources and personnel. (And the same is true about the US CDC.) But the COVID pandemic could have been a critical growth and learning opportunity. Going forward, it would be prudent to strengthen NCDC and use that entity as a platform for disease surveillance.

3.2. Viral Testing

Background. At the start of the pandemic, testing employed real-time reverse transcription-polymerase chain reaction (RTPCR or PCR) techniques that amplify viral fragments in biospecimens to facilitate the identification of those fragments. This revolutionary technology has been used to identify past viral infections such as SARS, another coronavirus. It is unsurprising that this technology was the first deployed to test for ongoing COVID infection.

Implications. PCR testing has both advantages and disadvantages. The main advantage is sensitivity. PCR tests on nasopharyngeal swabs have a clinical sensitivity of roughly 80 percent. (Laboratory accuracy is even higher, but clinical accuracy, which accounts for sample-taking errors, are more relevant for practice. RTPCR tests are more sensitive than rapid antigen tests, which emerged later in the pandemic.) RTPCR tests are also highly specific when compared to tests on samples with no prior infection or infection with other coronaviruses.

The main disadvantage of RTPCR is that it is not very specific for ongoing versus cleared infection. Because RTPCR looks for viral fragments, it may give a positive result even after the immune system has overcome a COVID infection. Just as there may be dead soldiers on the field after a battle, there may be viral fragments in sputum after a successful immune response. This affects the interpretation of RTPCR positivity rates and infection rates.

A further problem with RTPCR is that it measures flow rather than the stock of infection and does not clarify the risk from that flow. Let us assume away for a moment that the government had conducted RTPCR tests on a representative sample of the population, notwithstanding the discussion in sub-section 3.1. Even then, RTPCR provides an imperfect measure of future risk. The reason is that it provides a measure of the fraction of the population that is currently infected, but the risk that that number poses depends on how many people were infected in the past.

This logic is best illustrated in the context of a susceptible-infected-recovered (SIR) compartmental model. Although the SIR model may not be appropriate to use when a virus mutates, it is insightful in the short run before a new variant arrives and helps illustrate a problem that is shared by models that account for viral evolution. The basic equations that describe this model are given below.

$dS/dt = -bSI$

$dl/dt = bSI-gI$

$dR/dt = gl$

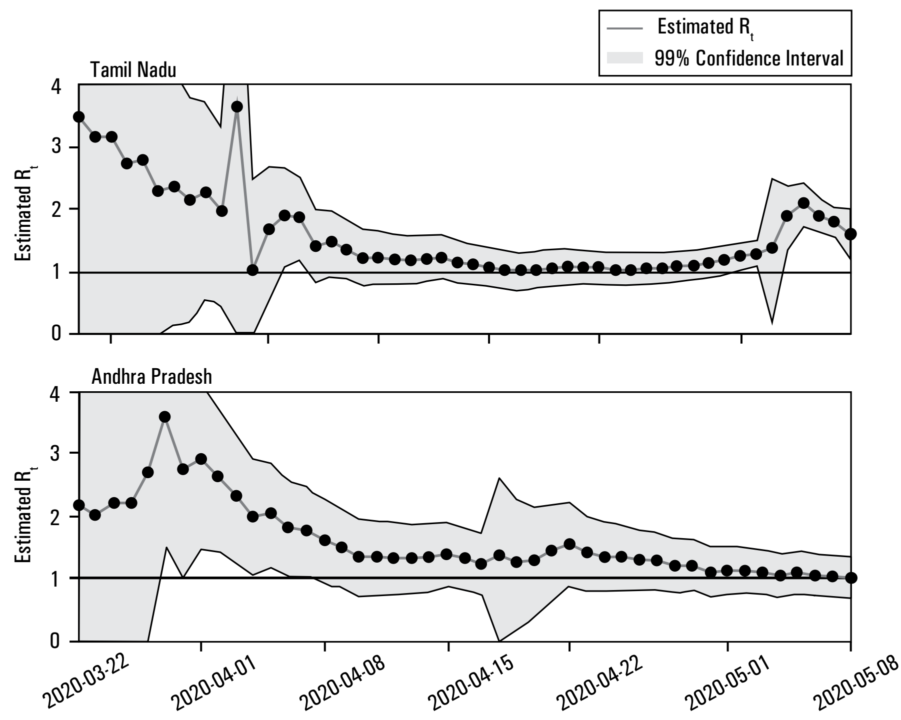
where S is the fraction of the population that is susceptible to infection, I is the fraction that is infected, R is the fraction recovered, b is the transmission rate, and g is the recovery rate.

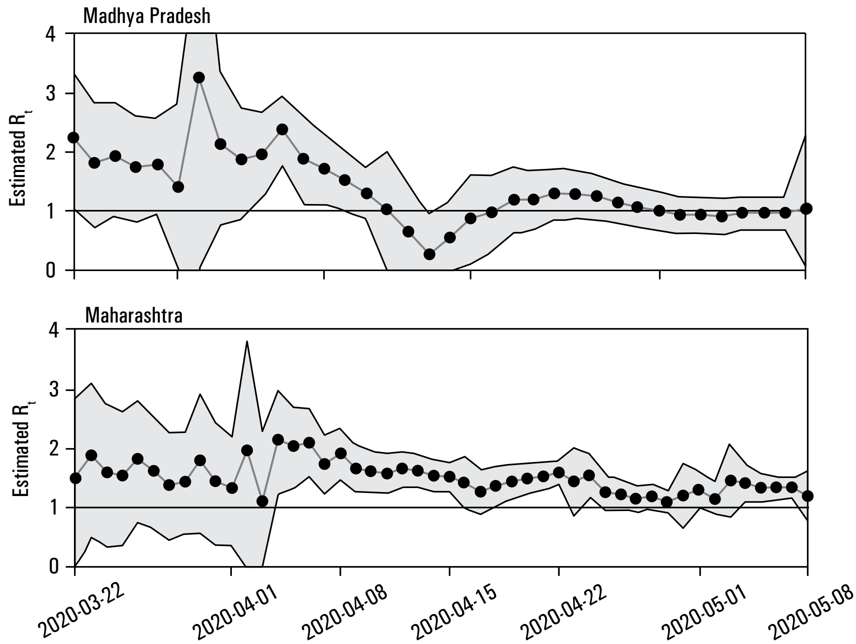
The key insight of this model is that the (basic) reproductive rate of the infection at the onset of the epidemic is $R_0 = b/g$, but as the epidemic progresses the (current) reproductive rate becomes bS/g, which falls with S as the epidemic progresses. Intuitively, the number of people an infected person can herself infect increases in the number of people who are susceptible. The number of susceptible persons falls as an epidemic progresses, so the risk from a given level of infection falls with time. To get a more accurate measure of risk requires knowledge of the fraction of people who remain susceptible. That is equivalent to 1 minus the fraction of people who are currently infected and the fraction that has recovered from infection. The fraction recovered is proportional to the number of people who were previously infected, i.e., the stock rather than the flow of infected.

One might suspect that one can simply examine the trend infection rates to glean future risk. To some extent that is true: in an SIR model, infection rates look like a bell curve, with the level of risk from a given level of infection depending on whether one has reached the peak of the infection rate curve or not. The problem is that the SIR model is a useful tool for understanding the logic of infection but does not accurately describe reality. First, the SIR model motivates policies such as lockdowns, which are thought to "flatten the curve" and buy time for building hospital capacity. But this very flattening complicates the identification of the peak of the infection curve. Relatedly, the SIR model does not account for human behavioral responses. Economists have shown that incorporating individual precautions into an SIR model causes a flattening of the infection curve just as a lockdown might (Toxvaerd 2020; Gans 2022 #5538). (I will explore this model in subsection 3A.) Second, the SIR model is appropriate for a non-mutating virus. But SARS-CoV-2 does mutate and at a rapid clip. In that scenario, there is a future risk of a jump in infection rates even if the infection rate is currently trending downwards.

Reforms. Two things can address the shortcoming of measuring current infection rates. First, one should couple estimates of infection rates with a model of infection that allows one to measure current reproductive rates. Using this approach, one can use past infection rates and an assumption about the recovery rate g to estimate current reproductive rates. Along with colleagues such as Satej Soman, Luis Bettencourt, and Vaidehi Tandel (Malani et al. 2020c), I used this approach to provide estimates of district- and ward-level reproductive rates to various Indian jurisdictions during the early course of the epidemic (see for example Figure 2).

FIGURE 2. Estimated Reproductive Rate, by State





Source and Notes: Figure and notes are taken from Figure 3 in Malani et al. (2020c). Data range from 11 March 2020 to 11 May 2020. Code and files available at https://github.com/mansueto-institute/ covin-c2-adaptive-control-wp.

Second, one can more directly estimate the number recovered by estimating the prevalence of anti-COVID antibodies or cellular immunity to COVID. That would enable a direct adjustment to the basic reproduction number to obtain the current reproduction number and forward-looking estimate of risk in different locales. I will discuss serological surveillance and cellular immunity later in this paper.

3.3. Cases versus Positivity Rate

Background. From the very beginning of the pandemic, the government has reported the number of positive tests. To convert that into an infection rate, a more informative statistic for both epidemiology and policy, one needs to have a denominator. A tempting approach is to divide by the number of tests conducted. This was not always easy to obtain, as testing rates were not always reported by the government. But even when they were, they did not always produce a useful measure of infection rates.

It is possible that the government did not report testing rates because they did not track them. In the rush of the pandemic, perhaps only the most important administrative tasks were required. Perhaps this prioritization required a positive test to be reported, but not a negative one. As a result, testing rates were scarcely reported at the very start of the pandemic. One can see this by examining data on testing rates prior to June 2020 on www.covid19bharat.org.

Even after testing rates began to be reported, it was not easy to estimate infection rates because testing was not random. As mentioned above, testing focused on symptomatic individuals, who were more likely to be infected. Thus, the positivity rate was possibly an overestimate of the infection rate. At the same time, the positivity rate was used to inform the testing rate. If the positivity rate got too high, officials demanded more testing. If the targeted positivity rate ended up below the actual infection rate, testing might yield an underestimate of the infection rate. In any case, when sampling is conditioned on the outcome of sampling, sample statistics are not unbiased for population parameters.

Reforms. Perhaps the best that can be done under these circumstances is to, first, ensure testing rates do not depend on testing outcomes. To the extent they must, they should do so only periodically, and changes should be announced so that estimates do not accidentally mistake attribute changes in testing rates to changes in infection rates.

Second, though non-random sampling means that one cannot obtain unbiased estimates of the infection rate, one might be able to obtain, for short periods, reasonable estimates of the trend in the infection rate. Specifically, if (a) during some interval the testing rate and the testing policy is unchanged, and (b) it is reasonable to assume that trends in the sampled and unsampled population (e.g., among symptomatic and asymptomatic people) are the same, then changes in the positivity rate are informative about changes in the infection rate in that interval. The first assumption motivates the policy recommendation in the last paragraph. The second assumption is not unreasonable if the probability of whether a person is symptomatic does not depend on whether the person who infected her was symptomatic and the fraction of infected persons who are symptomatic is constant over time. These conditions seem to hold for a given COVID variant.

Third, it is important to keep track of and report testing rates from the start of the pandemic. While this seems a trivial reform, it is hard to implement because the government may be loath to admit that it has a low testing rate at the start of a pandemic. The solution may be to build a peacetime testing infrastructure that would enable a reasonable rate of testing from the very start of a new pandemic.

3.4. Communication Policy

Background. India's initial, hospital-focused testing strategy may have reflected a desire to contain panic (Kurian 2020). The government repeatedly announced that there was no community transmission (Thacker 2020), when hindsight tells us this was false. These blinders-on and risk-minimizing strategies are typical for governments: information is controlled because it is assumed that the public will respond inappropriately to a threat. This tendency is evident not just in testing policy, but also in how the government controlled (i.e., delayed disclosure of) information from ICMR's serological surveys and about the quality of the COVAXIN vaccine.

This tendency to avoid transparency is problematic for four reasons. First, it presumes that the governments make good policy decisions. The large variation in policy response to the pandemic—compare the response of the UK to that of Sweden, of the United States to that of Australia and China—suggests that all governments do not always act optimally.

Second, it assumes that the public does not act responsibly on information about social risks. This is contradicted by experience. For example, empirical evidence suggests that lockdowns have not had much of an effect because individuals engage in voluntary social distancing even absent government lockdowns (Goolsbee and Syverson 2021). To be sure, there are many other examples, such as masking and vaccination, where the public does not seem to take adequate precautions. However, some of the public's behavior can be written off as a difference in risk preferences of public health officials and the public: public health officials value health more and economic activity less than the public.

Third, while it could be argued that the public does not fully internalize the infection externalities from its risk-taking, the government's incentives may also be imperfect. Governments will argue that they want to control information to limit panic. But controlling information also allows them to limit criticism of their policy response to the pandemic.

The most important reason to avoid censoring information, whether by not testing or by withholding results from testing, is that the public will come to distrust the government's statements. Whether due to investigative reporting by journalists or the inability of the government to forever hide reality, the public learned the true nature and extent of the pandemic. Once that happened, it is likely that the public inferred either that the government was poorly informed or that the government misinformed the public. Both inferences reduce the future credibility of government officials. That, in turn, means that future communications policy and crisis response may be less effective.

Reforms. To remedy public skepticism about government announcements concerning the current and future pandemics, the government should commit to real-time data gathering and disclosure of evidence about epidemics. It can do so in two ways.

First, it should announce a surveillance strategy and promptly and regularly release information obtained from surveillance. This strategy could be as simple as reporting (self-selected) hospitalizations and deaths or as complicated as conducting regular surveys of representative populations, as Tamil Nadu has done (Selvavinayagam et al. 2021). Moreover, it should provide regular and detailed data from its public data. It can take a cue from efforts such as covid19india.org and covid19bharat.org. Indeed, it is an indirect slight against the government that people rely on private efforts such as these websites (along with Johns Hopkins and Our World in Data), rather than governments or the WHO to track COVID. The advantage of regular and timely release of information is that individuals would know as soon as the government delayed a report that the government may be censoring information. Precisely because that delay would be so public, it would deter the government from interfering with data gathering or dissemination.

Second, the government should permit—even encourage—non-governmental and independent efforts to surveil for disease. These efforts could be by international organizations such as the UN or WHO, or from private companies and foundations. A good example, albeit of economic rather than health information, is the Centre for Monitoring Indian Economy's Consumer Pyramids Household Survey (CPHS). Even when ostensible data quality concerns and the pandemic delayed government economic surveys, CPHS continued to inform the public about the state of the economy. The independence of these organizations both increases the credibility of the information they provide and may increase the credibility of government data if the latter produce similar inferences as private data.

3.5. Contact Tracing

Background. A second important tool – besides testing symptomatic cases at hospitals – that the MOH used to track and contain the epidemic at its start was contact tracing. Contact tracing has its origins in the late 1800s, when infectious diseases spread in western European cities that grew dramatically at the dawn of the Industrial Revolution. Contact tracing is shoe-leather epidemiology: it requires the intuitions of a sleuth, not mathematic modeler. Individuals who test positive via, say, symptomatic surveillance, are asked about their contacts. Then health workers go out and interview and test those contacts. The process is repeated with each contact that tests positive. Each person who is positive is also asked to quarantine to limit the number of new infections they cause. (I will defer discussion of quarantining to the next subsection.) In this manner, contact tracing is ostensibly a method of measuring the spread of infection even as one controls the spread of that infection.

For slow-spreading and purely symptomatic infections, contact tracing can be an effective method of limiting an infection. But when the infection has a high reproductive number – the R_0 for even the wild variant of SARS-Cov-2 was 2 to 4 (D'Arienzo and Coniglio 2020) – contact tracing requires a massive, trained labor force and testing capacity, both of which are scarce at the start of an epidemic. Moreover, scarcity of testing means mainly symptomatic individuals were tested and quarantined. Asymptomatic infection escaped the net. In short, contact tracing is too slow to prevent the spread of a highly contagious infection.

Nor is contact tracing particularly effective at measuring the spread of an infection like SARS-CoV-2. From a statistical perspective, contact tracing employs a type of snowball sampling. But without knowing ex ante the process and rate of selection into infection, snowball sampling does not yield a representative sample and thus unbiased estimates of population parameters such as infection rates (Parker et al. 2019). Snowball sampling is even less effective when scarcity of testing (or misunderstanding about the infection) causes contact tracers to not test asymptomatic infections.

Reforms. That said, analysis of data from contact tracing efforts in Andhra Pradesh and Tamil Nadu did yield essential insights about the pandemic (Laxminarayan et al. 2020). The most important of these was that 5 percent of infections accounted for 80 percent of positive contacts (see also Endo et al. 2020). While most discussions of modeling COVID focus on basic or current reproductive numbers, this finding suggests need for focusing on the so-called dispersion factor k in the distribution of reproductive rates across individuals.

An important consequence of high dispersion is that policies targeted at populations, such as lockdowns, are less effective than individually-targeted interventions such as quarantines (Lloyd-Smith et al. 2005). Governments around the world—including in India—failed to heed this early warning, even though it was highlighted at the start of the pandemic (Kupferschmidt 2020; Lewis 2021).

High dispersion also means that it is critical to identify the observable correlates of superspreading: why are some infected people superspreaders while others are not? Yet, little of this analysis has been done. It was certainly feasible: health authorities in India could have sampled superspreaders and non-superspreaders, and carefully analyzed how these two groups differed, whether in social environment or biology. As far as I know, this work has still not been conducted (Lewis 2021).

Ostensible political obstacles to individual-focused policies should be easy to overcome with appropriate messaging. Perhaps equity is a concern: individual-based policies require treating ostensibly like people differently. But that ship has sailed and COVID policies already distinguish between infected and uninfected people, younger and older people, and vaccinated and unvaccinated people. Distinguishing between individuals who are more and less likely to be superspreaders seems a small additional step. Perhaps privacy restrictions are an obstacle. However, the high economic and liberty costs of lockdowns suggest that perhaps people would be willing to trade some privacy to permit investigation of individual correlates of dispersion.

3.6. Quarantine

Background. In the early and middle stages of the pandemic, the government required individuals to quarantine if they tested positive. Famously, Mumbai re-purposed a cricket stadium to quarantine individuals who lived in dense housing that lacked the space for individual quarantine, i.e., individuals from slums (Express News Service 2020). The simple logic was that quarantining would limit the spread of infection.

While quarantine is a wise decision when all infected individuals are symptomatic and all symptomatic people are tested, it makes less sense when many of the infected are asymptomatic and testing is limited to symptomatic persons or when testing is voluntary. First, if asymptomatic individuals are not all tested for infection, there will be substantial spread of infection even if symptomatic cases are tested and quarantined.

Second, because quarantine is costly, even symptomatic people may avoid testing to avoid quarantine. As a result, many symptomatic persons will avoid quarantine and continue to infect the population. This is the same logic that leads countries to avoid reporting outbreaks: both governments and people will be deterred from obtaining information if that information entails a net cost.

One might argue that, on balance, quarantining is a good idea. Even if every infected person does not quarantine, the more infected people who do, the slower the disease will spread. Moreover, though quarantine may discourage some testing, there remains enough testing that quarantine slows the spread of disease more than a no-quarantine policy would.

Reforms. One could avoid the problem of discouraging testing if testing was on balance beneficial. Informing others may not be an adequate benefit because we are not all altruists. The typical reason for testing is access to therapy. However, until antivirals are widely available, therapeutics will not incentivize testing. Therefore, at the start of an epidemic, treatment is unlikely to incentivize testing (and thus quarantining).

An alternative benefit that could be used to encourage testing and quarantining is an exemption from lockdowns or mobility restrictions if one develops immunity. For example, if quarantining for ten days after a positive test provided a person a pass to circulate despite a lockdown or to travel between countries, that benefit might encourage testing. The problem is that governments were slow to grant immunity passports following natural infection. A reasonable concern was moral hazard: individuals might purposely infect themselves to obtain immunity passports. We do not have good evidence on either the extent to which quarantine deters testing or the extent to which immunity passports encourage infection. However, a fortuitous possibility is that quarantine will offset the incentive to become infected and immunity passports encourage testing.

4. The Lockdown

Roughly two months after its first COVID case, India suddenly announced one of the world's harshest lockdowns. It has been suggested that the government's decision was informed by early models suggesting the pandemic would infect hundreds of millions in the absence of a lockdown. It is unclear that the lockdown avoided those infections. Moreover, in cities it may have accelerated infections.

4.1. Disease Modeling

Background. Early in the pandemic, there was very little empirical data about the pandemic. However, that did not stop modelers from combining that meager information with models of exponential growth in disease to project scenarios that ranged from tens of millions infected to nearly a billion people infected (see, e.g., Singh and Adhikari 2020; Chatterjee et al. 2020; Wang 2020). It has been asserted that this work motivated India's lockdown (Wikipedia 2022).

With the exception of Chatterjee et al. (2020), all the models were created by scientists working abroad. Within the government, early projections were often based on polynomial projections using Excel and data on positive cases. One reason for this reliance on foreign experts is that India does not have a deep bench of mathematical biologists working on disease models. When the pandemic hit, the shortage of mathematical biologists became a global problem. As a result, many of the early modelers – in India and abroad – were computer scientists (e.g., Sandeep Juneja), mathematicians (e.g., Murad Banaji), physicists, and economists (e.g., Mudit Kapoor), who had mathematical and simulation skills and could quickly brush up on the structure of epidemiological models.

Implications. Mudit Kapoor, working with NITI Aayog to evaluate these models, asked me for my evaluation of these models. I referred the question to a group of physicists and engineers at MIT, who tried to stress test the models. They raised two concerns (Figueroa et al. 2020).

The first was that some of the models were not transparent. They specified no equations or parameter values. To evaluate the credibility of models, one needs to know what goes into them. Without clarification about inputs, one could not be sure whether the model's output was credible or made up.

Second, the models were extremely fickle. Pandemic disease follows an exponential process. Small changes in parameters could have huge impacts on predictions. The median estimate of the basic reproductive number (R_0) for the original variant of SARS-CoV-2 was 3. That implies that each current infection would produce three future infections. But the range for the virus's R_0 was 2-4. Assuming a ten-day recovery, let us suppose new infections are generated in five days. Then in a given month, each infection could lead to either 64 (2^6) or 4096 (4^6) infections.

An important implication is that the error on forecasts rises with time. The error in one month out of four is the right R_0 but instead when two is used (or vice versa), it is roughly 4000 cases. Two months out the error is over 16 million! If we use a 1 percent death rate, the error is 40 deaths in one month but 167,731 deaths in two months. And all from just one infection!

Despite the extreme sensitivity of disease model forecasts, there was little surveillance and thus data to support the parameters plugged into the early models, and yet the models were used to make forecasts months out.

A third concern, raised by economists, is that none of the models considered the human behavioral response to the pandemic. The standard epidemiological model assumes that human behavior is unaffected by the occurrence of an epidemic. But that is false.

Individuals take precautions even when not forced to by the government. One piece of evidence is that, in the data on COVID, the current reproductive number (R_t) lingers at 1 for extended periods of time (even outside the context of a lockdown). See, e.g., Figure 3, using data from the US. The workhorse SIR model in epidemiology cannot explain this behavior.[2] (Nor can simpler Gaussian models. A susceptible-infected or SI model, can generate periods of R_t=1, but it has other problems, which I will discuss below.) But simple economic models that couple the SIR model with humans that choose activity levels to balance health and the benefits of activity do generate the prediction that R_t lingers at 1 (Gans 2022). Another piece of evidence is the failure of empirical work that adequately accounts for voluntary social distancing to find big impacts from lockdown (see, e.g., Goolsbee and Syverson 2021).

Once human behavior is included in the SIR models, the models predict that, instead of a single peak in infections, there is an extended plateau (Toxvaerd 2020; Gans 2022); see Figure 4. The epidemic runs through the population, but at a slower rate. When the susceptible population falls so low that bS/g falls below 1, the R_t in the economic epidemiological model also begins to fall. To put it another way, the epidemic will follow the same qualitative pattern without a lockdown as it would if a lockdown were imposed, that is, human response flattens the curve even without a lockdown. The main difference between a lockdown and human response is that the lockdown might flatten the curve at a lower level of infection. However, this merely delays cases.

Reforms. India's early experience with disease modeling suggests two reforms. First, it is important that the country invest more in disease modeling, both in the government and in academia. It is critical that the investment be such that there are multiple groups that can critique each other and, in the process, improve each other's work. In addition, disease modeling should be an interdisciplinary activity. Epidemiologists should work with computer scientists and physicists, on the one hand, and social scientists, on the other. The former group will improve the robustness and computational efficiency of the disease model. The

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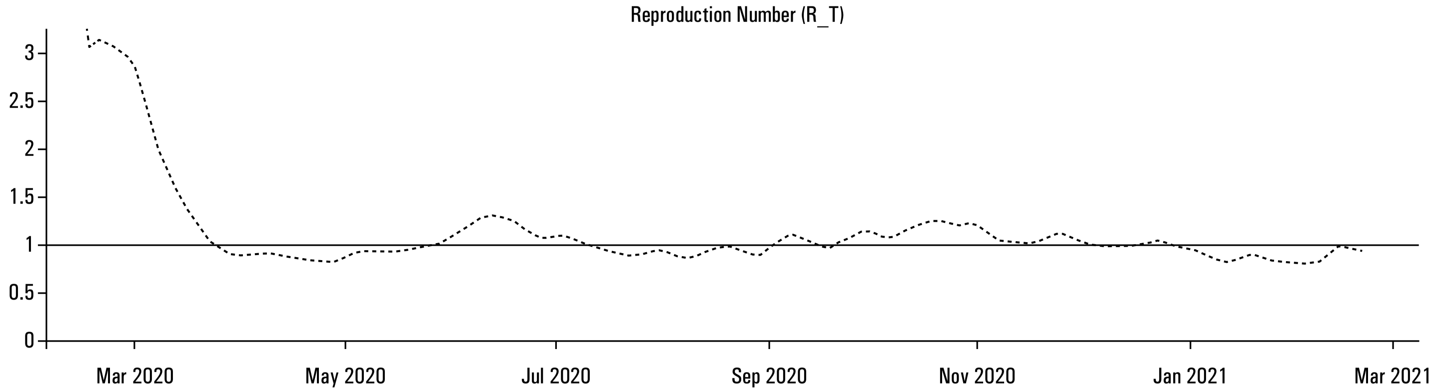
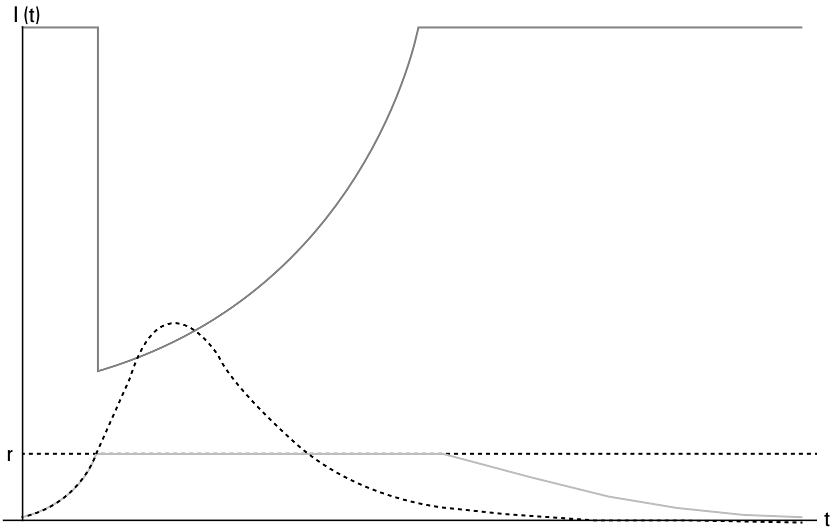
2. In a SIR model, R_t is equal to bS/g. The share of susceptibles S falls from 1 to some minimum level, perhaps 0, following a backward S curve. This implies that R_t passes through 1 but does not linger there. Even when S plateaus, R_t is not 1 because S only plateaus when I=0, so R_t is undefined.

FIGURE 3. Effective Reproduction Number (Rt) for United States, March 2020–March 2021



Source and Notes: Data cover 3 COVID-19 waves in the US. Rt estimates are based on deaths data. Figure is copied from Youyang Gu, https://covid19-projections.com/.

Figure 4. Equilibrium Disease Prevalence and Social Distancing across Stages of the Epidemic



Source and Note: This figure was generated by Flavio Toxvaerd based on Toxvaerd (2020). The dashed line shows infections in an SIR model without human behavioral response, the light grey line curve shows disease prevalence I(t) with voluntary social distancing, and the dark grey line curve shows exposure (1-d(t)).

latter group will help correct the biggest error in disease models, which is the failure to account for human behavioral response.

Second, disease modelers, and their government audience, should be more careful with their forecasts. For one thing, there must be greater effort to improve the fit of models to reality by continuously updating parameters that are inputs into the models. Since exponential models are so sensitive to parameter values, extra care must be taken to ensure that those parameter estimates are continually revised. Only one of the models initially presented to the government continually updated parameter estimates—the one out of the University of Michigan (Wang et al. 2020). Bhramar Mukherjee's laboratory admirably took the baton from that group and continued providing updated parameters and forecasts throughout the pandemic. I worked with a team that included Luis Bettencourt and Satej Soman, that did the same for a few States during the pandemic. Our code is posted and can be used and modified by Indian groups who work on future pandemics.

Another precaution is that models should not be used for long-term projections. As noted, models with exponential disease growth are prone to massive errors even over a period of a few months. This is not to suggest that there may not be massive caseloads. Instead, it is a warning to account for extremely wide confidence intervals before making policy choices.

4.2. The Benefits and Costs of the Lockdown

Prime Minister Modi announced a one-day *janata* or voluntary lockdown and then, a day later, an indefinite national lockdown on 24 March 2020. That lockdown supplemented pre-existing travel restrictions and was among the harshest lockdowns declared around the world (Figure 5). As I explained above, a lockdown is a suppression policy that is both deeper (restricting more activity) than travel restrictions and broader (covering a larger geographic area) than containment zones or quarantines. In India's case, the lockdown was a stay-at-home policy combined with restrictions on non-essential businesses and supply chains. Disease and economic surveillance can be used to evaluate the efficacy and costs of the lockdown.

4.2.1. Benefits

A casual examination of case and death counts (Figure 5) yields mixed signals about the benefits of the lockdown. On the one hand, the lockdown did not prevent the rise in cases. On the other hand, cases did not rise until the lockdown was lifted. Perhaps the problem was that the lockdown was lifted too early. Alternatively, one might argue that the lockdown delayed a rise in cases and bought time for the government to bolster hospital capacity, reducing the mortality rate from infection.

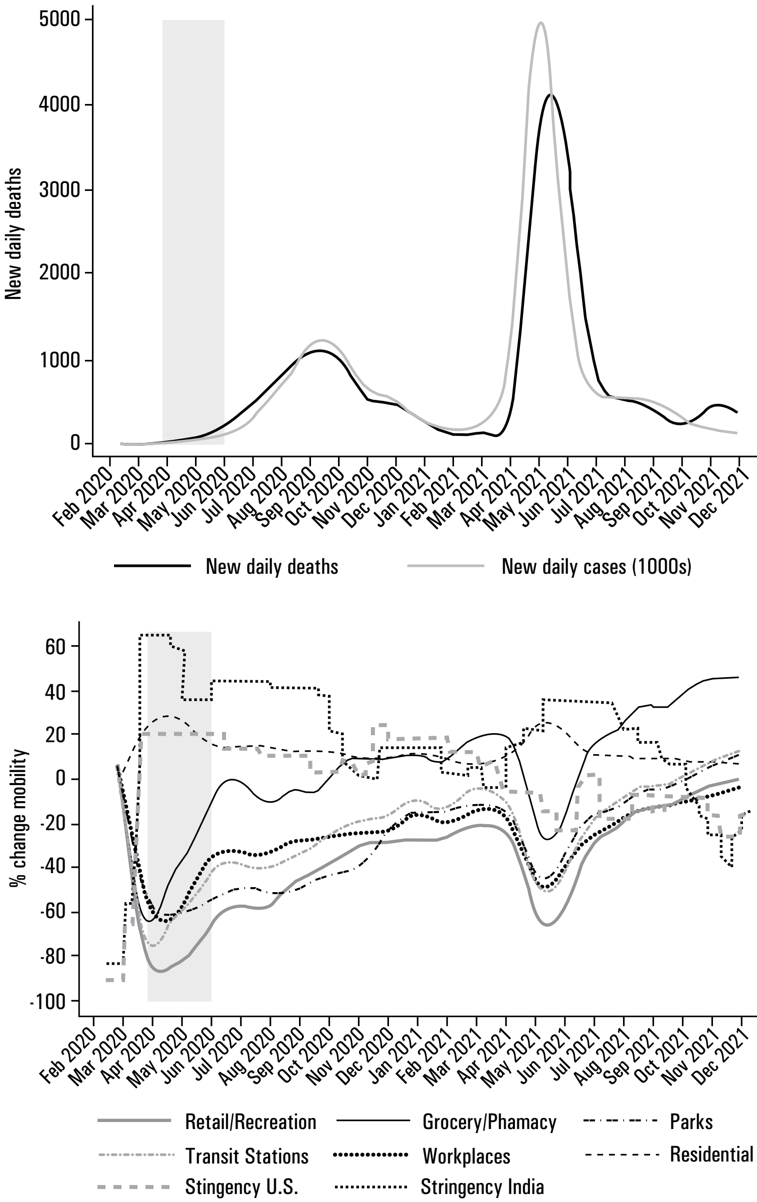
Amount of delay. There are several reasons to question the impact of the lockdown on delaying the growth of cases. First, economic theory suggests that there would have been a reduction in economic activity even in the absence of the lockdown. People would have voluntarily socially distanced to limit exposure to infection. That would also have delayed the peak in cases, to some extent, and bought time for the government to shore up testing and health care facilities.

Second, and more importantly, the benefits and costs of lockdown were distributed unevenly. A serological survey conducted in Mumbai found that roughly 55 percent of slum residents and 15 percent of non-slum residents had antibodies to COVID by July 2020, just five months into the epidemic (Malani et al. 2020b). This finding suggests that the lockdown may have slowed the pandemic outside of slums but accelerated it inside slums.

The logic emerges from two observations. First, slums are incredibly dense and non-slums are not. For example, the average distance between people in Dharavi, assuming people are evenly distributed, is less than 3 meters.[3] Actual distances are likely much smaller as walls prevent even spacing and people are

3. Dharavi has a population density of roughly 340,000 persons per square kilometer. Assuming that individual locations are uncorrelated, one can model the spatial distribution of people as a Poisson. The average distance between persons is then 1/(2 s), where 's' is the square root of population density per meter. See https://physics.stackexchange.com/questions/534272/what-is-the-relation-between-density-and-average-distance-to-nearest-neighbour.

FIGURE 5. COVID Trajectory, Severity of Lockdown, and Mobility Changes



Source and Notes: These figures and this note are copied from Figure A1 in Gupta et al. (2021b). Case and death data are from www.covid19India.org. We show aggregated daily reported cases and deaths from the government. The shaded period marks the national lockdown. Lockdown severity data are from Hale et al. (2020). Mobility data are from Google mobility reports (Google LLC 2021). The shaded period marks the national lockdown. Time periods cover February 2020–January 2021.

clustered into small homes. In contrast non-slums are nearly one-tenth as dense as slums. For example, nearly half of Mumbai's population lives in slums, but slums occupy just 12 percent of Mumbai's land. Second, on most days, a typical slum resident works as, e.g., a domestic laborer or construction worker in less dense non-slum Mumbai. So, during work hours, the density in slums falls and the density in non-slums rises.

When the lockdown was declared, it stopped work and thus increased daytime density in slums and reduced it in non-slums. It is plausible that this shutting down of work mobility accelerated the spread of infection in slums. Estimating the magnitude of this effect is difficult. We do not know the rate at which the pandemic would have spread if slums had less daytime interpersonal contact. Perhaps slums, even when residents left for work, had enough density at night for the infection to spread more rapidly in slums than non-slums. But the qualitative effect of the lockdown was to increase density and thus the disease burden in slums and lower it in non-slums.

Making use of delay. Moreover, it is unclear how much the lockdown improved pandemic preparedness. The MoHFW convened a COVID war-room that, among other things, began taking stock of and organizing bed capacity. Unfortunately, it is difficult to assess the impact because the resulting data on hospital facilities were not made public.

However, there are reasons to doubt that much could have been accomplished in the short run. First, India has very poor data on hospital capacity. Paul Novosad and Sam Asher attempted to examine data directly on bed capacity from DLHS-4 (2012–13) and the Population Census (2011), and indirectly on hospital employment from the Economic Census. (They tried but were unable to obtain Registry of Hospitals in Network of Insurance (ROHINI) data at the district level.) A surprising finding was that there was low correlation between the data sets on district-level hospital capacity, strong evidence of the poor data quality. Conducting a facilities census takes time in normal times, let alone a pandemic. Moreover, private facilities may be hesitant to report capacity to the MoHFW for fear of their facilities being seized for COVID care, crowding out private revenue from non-COVID cases.

Second, India had among the lowest rates of beds per capita prior to the pandemic (Nagarajan 2020),[4] and hospital capacity is a capital asset that is difficult to scale in the short run. In contrast to, say, China, India is not known for the ability to build infrastructure quickly. (That this limitation is common to many countries, including high-income countries, is little solace in a pandemic.) The best that could be done quickly is to revise bed allocations to (a) prioritize beds for COVID versus less urgent diagnoses, and (b) designate specialized COVID facilities to reduce the risk that hospitals spread COVID, a substantial

4. Novosad and Asher (unpublished memo on file with author) believed that even a 1 percent rate of (symptomatic) infection would overwhelm hospital capacity.

concern in prior pandemics like SARS (Bennett et al. (2015) and also with COVID (Ngandu et al. 2022). Again, due to lack of data, it is difficult to assess the progress made on these strategies during the lockdown.

4.2.2. Costs

To assess the cost of lockdown, I turn to economic surveillance. India does not have good, real-time monitoring of health care. For example, other countries have birth data, cause-specific mortality data, and insurance claims data, typically furnished by the government. These data are either not gathered or not released by governments in India.

Economic data. Better data are available for economic surveillance. Even here, though, we rely on private sector surveys as the government did not conduct surveys on household finance during the pandemic, as far as we know. One complication is that the lockdown shut down not just trade, but also in-person surveys.[5] This means that the data we employ are gathered using phone surveys, which may have different quality.

In my opinion, the best of these surveys is the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring Indian Economy. This is a household-level panel data set that includes roughly 175,000 households with nearly 1 million members. Data on each household is longitudinal, gathered every four months. Moreover, sampling is staggered so that data on a representative cross-section is available each month.

The CPHS data are not perfect: people criticize its use of random systematic sampling rather than random sampling from a census, sampling based on town-population strata rather than in proportion to specific town populations, and its possible oversampling of main streets (relative to side streets) in villages (Somanchi 2021).

However, the alternative to the CPHS is not better sampled data, but rather no data: there is no alternative available for the relevant time frame. Moreover, some of the critiques advocate sampling methods that are better for some uses, but worse for others. And by better, I mean higher power, not less bias. An implication is that CPHS has lower power than it could have for some uses. Even that weakness is overcome by its relatively large sample size. Finally, scholars are actively working on alternative weights to make CPHS comparable to pre-pandemic data sets like the NSS or Census (Sinha and van der Weide 2022).

The CPHS did not stop during lockdown. But it did switch from in-person to telephonic. Because the firm—in the interest of quality—used its managers

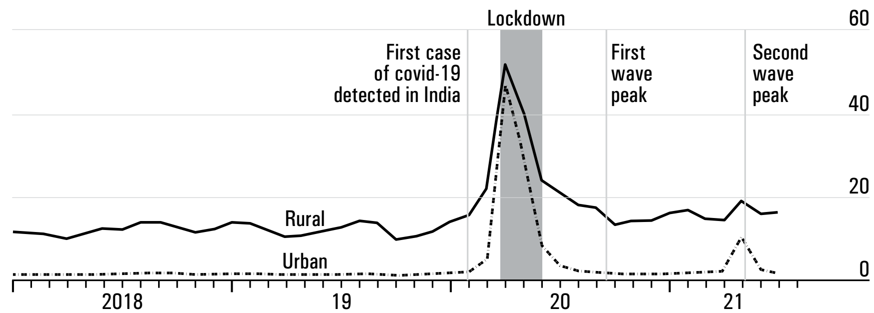
5. Lockdown also made disease surveillance difficult. Here is anecdotal evidence from serological surveillance by the State of Karnataka and advised by Manoj Mohanan, Anu Acharya, Kaushik Krishnan and I, from June to August 2020. Phlebotomists began surveillance in Bengaluru in June but had to finish early because of a lockdown declared in that city that barred them from collecting blood. We then returned later after the lockdown was lifted.

rather than door-to-door surveyors to conduct phone surveys, it could not survey all households. Managers were given a list of phone numbers in their jurisdictions but no other survey data on numbers and asked to sample roughly half the households in each jurisdiction, preserving the urban-rural balance.

While the selection was not formally random, work by Arpit Gupta, Bartek Woda and me (Gupta et al. 2021a) suggests that a LASSO-selected prediction model using the previous rounds data on households could explain at most 1 percent of the variation in selection for telephonic surveys. Non-response to telephonic surveys resulted in an overall response rate of 35 percent of the formal sample, in contrast to the usual 85 percent response rate pre-COVID. After the lockdown, sample response rates rose to about 75 percent.

Poverty and inequality. The CPHS data show that poverty and inequality spiked during the lockdown. Using the World Bank's $1.90 per day measure, the extreme poverty rate (measured by income) spiked from 2 percent to nearly 52 percent in urban areas (Figure 6). Rural areas started poorer but experienced a similar spike: from 12 percent to 47 percent. After the lockdown, poverty declined to 2 percent in urban areas, but was 14 percent in rural areas.

FIGURE 6. Share of People in Extreme Poverty (Percent)

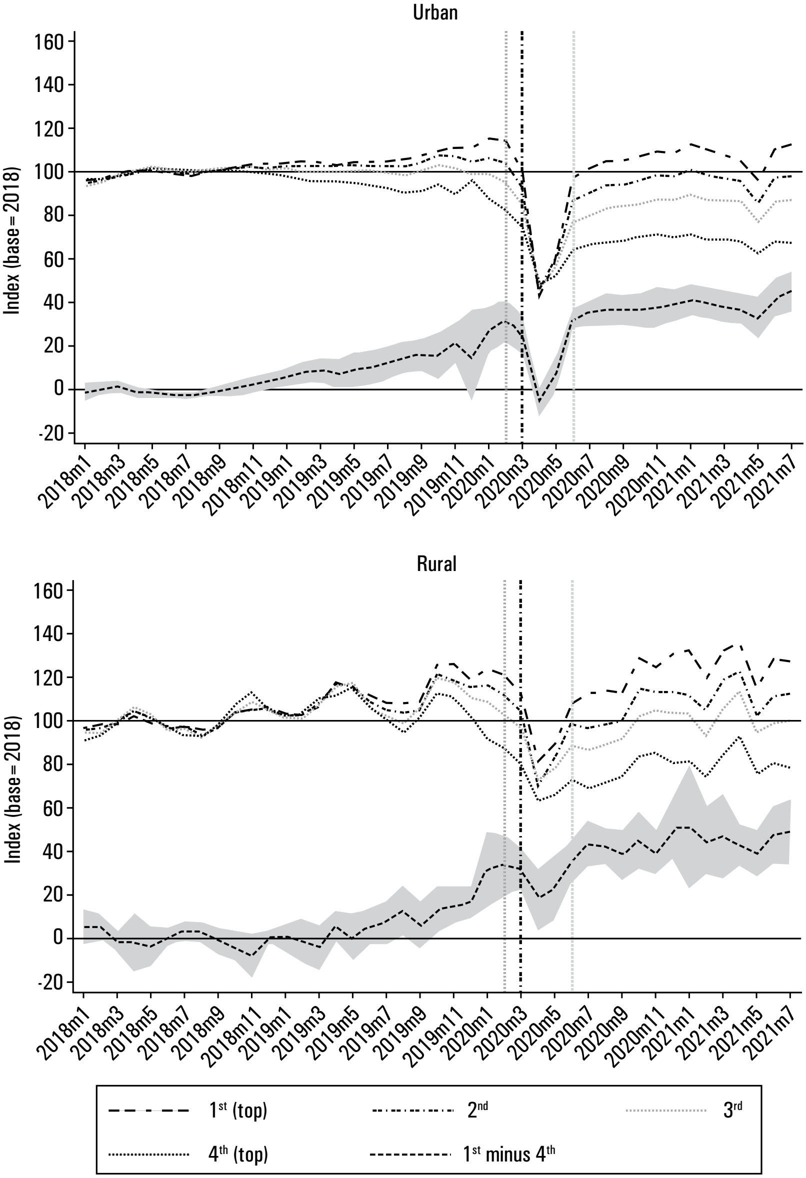


Source and Notes: Extreme poverty is defined as consumption below $1.90 on a PPP basis. Consumption data is from CPHS. PPP data is from IMF. This figure is copied from (Economist Daily Chart 2022), based on data provided by (Gupta et al. 2021b).

I measure inequality in two steps. First, I normalize individual monthly income by an individual average income in 2018 and then sort individuals into quartiles based on their 2018 income. Second, I subtract the average monthly normalized income in the top quartile of income earners from that in the bottom quartile of income. The higher is this measure of inequality, the less is the inequality. The level of this index measure percentage point changes in inequality.

Figure 7 shows that inequality had been falling since 2018. When the pandemic hit, that trend reversed a bit in urban areas. But when the lockdown

FIGURE 7. Normalized Income over Time (2018 Baseline)



Source and Notes: This figure is taken from Figure 1B in Gupta et al. (2021b). Data are from the CPHS. The figure plots the fixed effects (lines) and quartile x month fixed effects estimated by using a regression of normalized income on quartile x month fixed effects. The lines are the equivalent of the weighted average of per-capita income within income quartiles in each State x urban status location, using individual member weights from CPHS. The units are an index where 100 is average 2018 income of a person. The dashed line at the bottom indicates the difference between the first- and fourth-quartile index for income, measuring the decline in inequality in percentage points. Shaded area is the 95% confidence interval around a statistic. Dashed vertical lines in February 2020, March 2020, and June 2020 indicate the first month of the pandemic (left vertical line), the month the national lockdown started (middle vertical line), and the month the national lockdown ended (right vertical line).

was declared, all the gains since 2018 were erased. Both the effects were less pronounced in rural areas. This is a lockdown-specific effect because, once the lockdown ended, inequality returned to pre-pandemic levels. This finding is not specific to my specific measure of inequality. As Gupta et al. (2021b) show, the Gini coefficient also spiked during the lockdown.

Consumption effects were less severe. Gupta et al. (2021a) show that the median consumption did not fall as much as the median income. Households were equally able to smooth consumption after idiosyncratic income shocks remained the same before and after the pandemic, and across income classes. The Marginal propensity to consume remained roughly 10 percent. However, households faced a larger aggregate shock than consumption did respond to that. Nevertheless, consistent with Engel's law, households were able to increase the food (and fuel) share of their income to protect against hunger.

4.2.3. Lessons

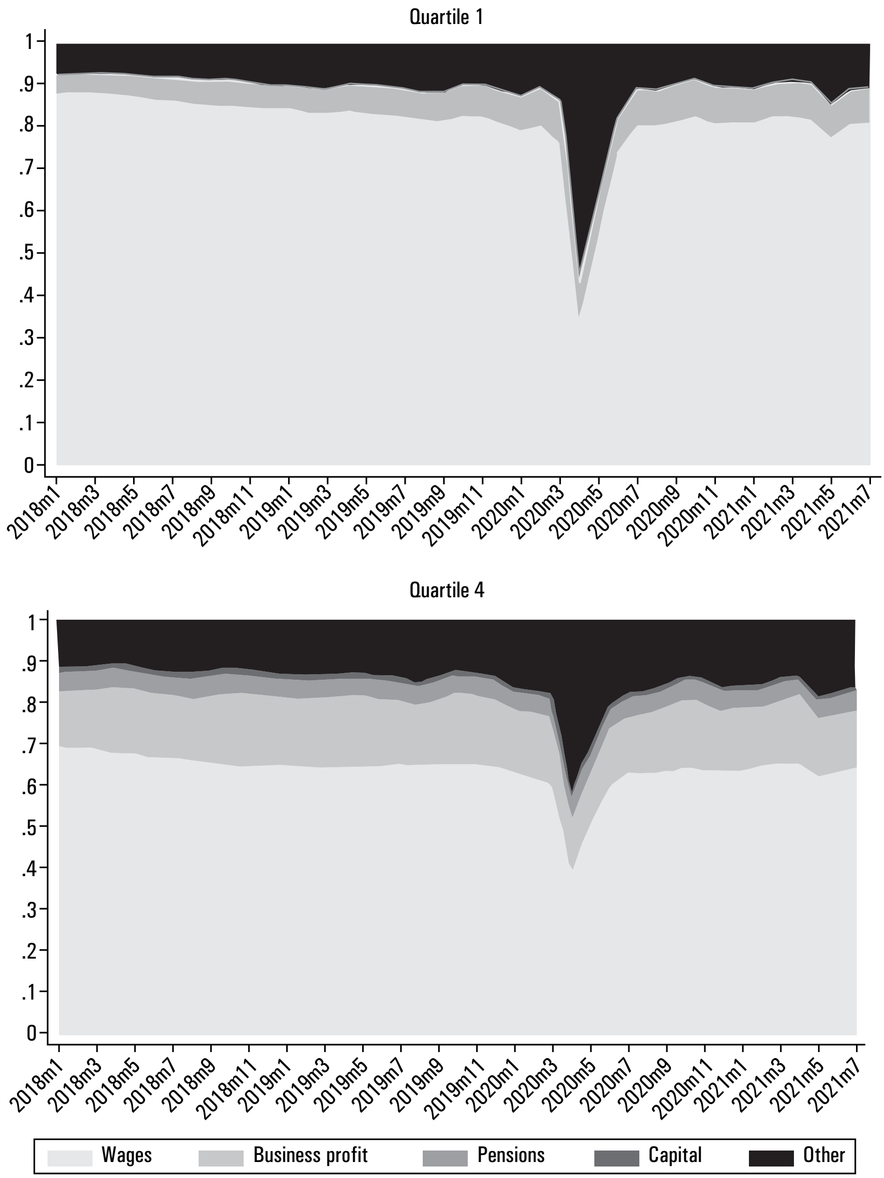
India's experience with the lockdown was not unique. Many nations imposed harsh but short-lived lockdowns at the start of the pandemic. They were lifted in part because of how disruptive they are. The V-shaped economic recovery in economies across the world are proof of this pattern.

There are several lessons in that common experience. First, once it was confirmed that the reproductive rate of the new infectious disease had a high level of dispersion, countries should have abandoned lockdowns and instead targeted suppression at highly infectious people (Lloyd-Smith et al. 2005). Narrower, targeted suppression may have achieved the same disease control with less economic impact. Moreover, there may have been greater support for keeping those restrictions in place. Financial compensation for those individuals subject to targeted suppression could have overcome political and ethical opposition to those measures.

Second, urban lockdowns seem especially inequitable. They may hasten disease spread among slum-dwellers, who live in poor communities that have above average density. Perhaps cities should abandon urban lockdowns unless an infection does not have serious health consequences, the population has developed immunity to the infection, or governments can substantially increase supply of health care to slums during a pandemic.

Third, if targeted lockdowns are not possible, lockdowns should be accompanied by social programs to ensure that spiking poverty does not lead to hunger and associated mortality. It would be a shame to replace mortality from infection with mortality from famine. Households will attempt to protect themselves. But if savings are low, then the government should step in to provide a safety net. If food supply is not constrained, cash transfers may be enough. If supply is constrained, perhaps by lockdown, focus should be on ensuring that essential services like agriculture are effectively exempted. The CPHS evidence suggests India's lockdown successfully exempted agricultural production so

FIGURE 8. Sources of Income for the Top (1) and Bottom (4) Quartile of Individuals over Time, with Government Transfers Reported in "Other"



Source and Notes: Figure and note taken from Figure 4 in Gupta et al. (2021b). Share of income is from different income sources. Capital income includes dividends, interest, rent, sale of assets outside of pension accounts. Other income includes government transfers, private transfers, value of agricultural goods produced for self-consumption, lottery winnings, insurance payouts.

that households were able to obtain food. Likewise, India increased transfers, especially to the poor, as Figure 8 indicates.

Finally, it may be that the cost of lockdowns is greater than the benefit. Voluntary social distancing may also flatten the curve of cases. Moreover, it may have less negative economic effects, especially on the poor. The difference between mandatory and voluntary distancing is that individuals choose the amount of risk they abjure based on personal circumstances. This frees the poor to continue working if their economic losses outweigh the health gains from distancing. Some may object that this imposes health costs on the poor, but that view fails to account for the fact that the poor may care about both health and non-health consumption.

Three pieces of evidence support the tradeoff implied by voluntary distancing. First, voluntary distancing had fewer negative impacts on economic welfare. Mobility remained suppressed even after the national lockdown (Figure 5), but poverty fell to nearly pre-pandemic levels and inequality resumed its pre-pandemic downward trend (Figure 6).

Second, cases did not rise immediately after the lockdown was lifted. The peak of the first wave occurred in September, more than three months after the lockdown ended (Figure 5). One cannot disentangle the effect of mandatory versus voluntary lockdown on the delay. But the data on symptomatic cases is also consistent with voluntary distancing keeping the peak at bay.

5. Later Stage Surveillance

5.1. Serological Testing

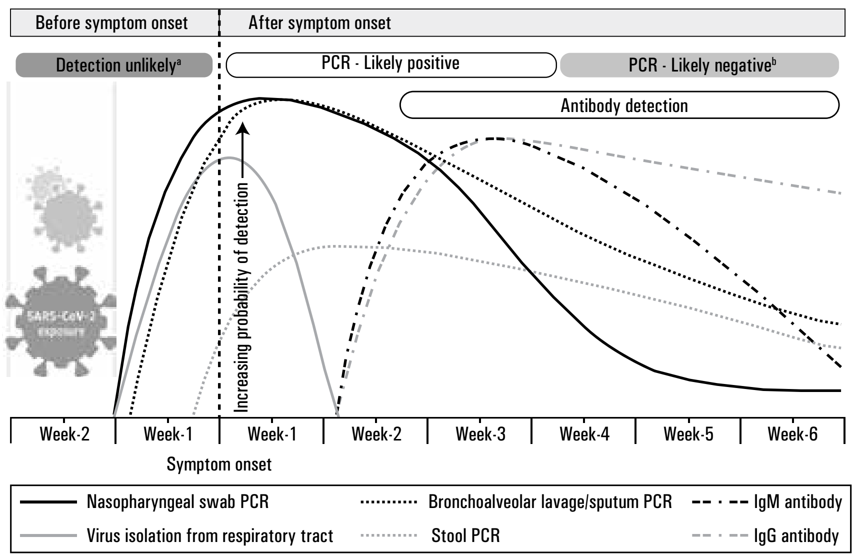
After India's lockdown, the focus of surveillance shifted from purely antigenic surveillance to also conducting serological surveillance for anti-COVID antibodies. Serological surveillance involves gathering blood and testing it for antibodies to SARS-CoV-2.

This qualitative expansion of surveillance happened for two reasons. First, the government restricted viral testing on symptomatic cases but did not restrict serological surveillance, in part because it did not have diagnostic value. The presence of antibodies indicates prior and likely cleared infection. Neither quarantine, ventilation nor antivirals are helpful. This difference in restrictions on testing is evidence of the impact of having medical doctors rather than public health officials in charge of surveillance: antigenic surveillance was restricted based on diagnostic value, while serological testing was not.

Second, antigenic testing, especially if limited in quantity or if asymptomatic cases are not tested, cannot inform population immunity and thus future risk. Antigenic testing signals current infection, especially at low cycles or equivalently high concentrations. One cannot simply count up prior cases to get the stock of people with immunity if not everyone can get tested or testing is restricted to symptomatic cases. (Though the restriction may be a product of limited supply.)

The main advantage of serological surveillance is that it can measure, at least for several months, recovery from infection. In contrast, antigenic testing with, for example, RTPCR can only detect cleared infection for 2-3 weeks after infection (Figure 9). Since population-level susceptibility to infection is declining as a function of the share that are recovered, serological testing provides better measures of forward-looking risk to public health. The latter is critical for planning suppression policy and vaccination campaigns.

FIGURE 9. Diagnostic Detection of SARS-CoV-2 and Associated Antibodies over Time



Source and Notes: This figure is copied from Sethuraman et al. (2020), While this figure focuses on individuals with symptoms, individuals without symptoms have a similar time profile, though the PCR negative period may be shorter and the level of antibodies may be lower.

5.1.1. Nature of Serological Tests

Serological tests vary along two dimensions. One is whether the test is a rapid test or a laboratory test. A rapid test can be implemented with minimal blood (dried blood spots) and gives answers quickly in the field. However, there are drawbacks. The sensitivity (probability a truly positive case yields a positive test result) and specificity (the probability a truly negative case yields a negative test result) of tests is lower.[6] Some of the time gain from rapid results (as opposed to venous blood draws) is lost by having to wait for test results in the field to record them. Moreover, it is difficult to ensure that surveyors wait long enough to correctly interpret test results when recording them.

A laboratory test has a higher accuracy. However, it requires a venous blood draw. Although one might suspect a high non-consent rate, we found reasonable consent rate in our work in Mumbai and Karnataka. This could be a product of heightened concerns about the pandemic at its start. Another drawback is the need to maintain a cold chain: the blood must be kept refrigerated from the field to the laboratory. This is an especially challenging problem in rural areas.

A second dimension along which serological tests, in particular laboratory tests,[7] vary is the method of lab test conducted. There are usually three options available. The gold standard test looks for neutralizing antibodies, i.e., antibodies that prevent the virus from entering a human cell. These are antibodies that attach to proteins on the face of a virus that the virus uses to cleave a cell. (The alternative is antibodies that attach to the virus, do not prevent it from entering a human cell, but do serve as a beacon for other immune system agents, such as white blood cells, to find and attack viral particles.) Neutralizing antibody tests are desirable because scientists know for sure that these antibodies are protective for humans. Other antibodies may or may not be good beacons depending on how well they attach to SARS-CoV-2 or how effective other immune system agents are at locating the beacon or killing any virus they find.

The second-best test is an enzyme-linked immunoassay or ELISA test. These have relatively high sensitivity, but for all SARS-CoV-2-related antibodies. As such they may not be as reliable a measure of immune function against COVID. A compensating differential is that these tests are less expensive and take less time than neutralizing antibody tests. That said, these tests do not have a natural unit, e.g., antibody concentration, unless they are done at different dilutions, which add to the time and expense required for these tests.

The third-best tests are chemiluminescent immunoassay or CLIA tests.[8] A laboratory can complete these tests more quickly than ELISA tests.

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6. Moreover, accuracy might vary across lots of the same test. We abandoned the regulatorily approved rapid tests in our work in Karnataka because when we tried to validate the rapid tests we obtained, we found they were less accurate than reported accuracy rates from the manufacturer. This is not a problem with laboratory tests as laboratories usually create controls for each batch of reagent by, for example, including a placebo in one row of wells per coated plate.

7. Rapid tests are usually chemiluminescent immunoassay or CLIA tests. After adding a sample, a colored line appears if the test is positive, i.e., a chemical reaction creates luminescence or distinct (reflection of) light waves. However, there are also now FDA-approved rapid tests for neutralizing antibodies. We employed these in a study in the slums and non-slums of Bengaluru for a project whose data is currently being analyzed.

8. Both ELISA and CLIE tests require specific machines, an important fixed cost. Their availability at local labs affects transport costs for samples.

They may have lower sensitivity than ELISA tests but have reasonable specificity.[9]

5.1.2. Obstacles to Obtaining Serological Tests

Despite the relevance of serological testing for pandemic policy, there were two policy obstacles to such surveillance, especially with rapid antibody tests.

First, rather than the Central Drugs Standard Control Organisation (CDSCO), ICMR took control of diagnostic test approval. Initially ICMR was skeptical of rapid antibody tests because of poor sensitivity and specificity. That objection makes sense for diagnostic tests used primarily for managing patient treatment. However, it does not make sense for tests used for population-level surveillance and policy. One can use statistical methods, like the Rogan-Gladden formula (Rogan and Gladen 1978), to obtain unbiased[10] estimates of population-level prevalence even with individually inaccurate tests.

As a result of this regulatory uncertainty, our surveillance efforts turned to more cumbersome lab tests. Even there we found that it was difficult to find private labs that had approval to conduct COVID tests. Certain COVID testing required heightened safety protocols. While several labs had submitted applications for licensing their safety, regulatory authorities were unable to act on those in an expeditious manner that reflected the urgency of the pandemic.

Second, the Central Board of Indirect Taxes and Customs (CBIC or the Board), functioning under the Department of Revenue in the Ministry of Finance, continued to impose tariffs on testing products even as the epidemic was growing and there were either no domestically produced tests or a shortage of such tests. A rumor we heard when trying to import tests early in the pandemic is that authorities were hoping tariffs would promote domestic production of tests. A pandemic that risked tens or hundreds of thousands of Indian lives is perhaps too high a price to pay for import substitution. Ultimately, though with some delay, foreign companies set up domestic partnership to produce their rapid tests locally and some domestic firms began producing their own rapid tests.

5.1.3. Implementation of Surveillance

Once serological tests were obtained, a statistical challenge emerged: how to obtain representative samples on which to conduct tests. For testing to give

9. The initial results from the serological study in Mumbai employed CLIA tests because of speed; these tests were later validated with ELISA tests, though those results have not been reported. Our sero-survey in Karnataka employed ELISA tests because we had more time to complete the laboratory work. Finally, an ongoing analysis of samples from slum and non-slums of Bengaluru employed both ELISA and rapid neutralizing antibody assays to provide multiple benchmarks for the main goal of that study, which is to measure cellular immunity.

10. A minimum level of accuracy (e.g., a positive case more likely than not to show a positive result) is required for these to assess the variance of estimates of seroprevalence.

us reliable estimates of population-level immunity, the samples need to be representative of the population.

Early on we tried to obtain representative samples by obtaining a census of all people and selecting a random sample from that census. It is too hard to conduct a census during a pandemic, so we turned to a pre-existing public census: voting rolls. Our strategy was to randomly select voting booth rolls and then randomly select individuals from those rolls. This effort proved difficult as the data were in poor shape. Many rolls were not in electronic form or not in English. Individual names and addresses were not always accurate. And the young were excluded from those rolls.

A second, more promising approach was systematic random sampling from random starting points. In the Mumbai serological survey, the team conducted systematic sampling from random starting points in slums and non-slums (Malaniet al. 2020b). In the four rounds of the Tamil Nadu serological survey, the State conducted systematic random sampling from randomly selected villages and towns in each district (Selvavinayagam et al. 2021).

There are two logistical problems with systematic random sampling. One is that, because sampling does not start with a census, the survey must collect data on family composition to generate weights that ensure that the weighted demographic composition of sample matches that of the population. The other is that random starting points must be selected from physical areas that are populated with humans. This requires a map with the universe of settlements. Such maps do not always track slums and nomadic tribals well.

A third approach is to use a pre-existing representative sample, usually a government sample based on a random draw from a census or a private sample that used a pre-pandemic systematic sampling exercise. In the Karnataka serological survey, the team used a representative sample from an existing survey frame (CPHS), which in turn, used systematic sampling (Mohanan et al. 2021). (The team approached other organizations for the right to use their sample but were unsuccessful.)

5.1.4. Lessons from Serological Surveillance

I was involved in four major serological surveys: the study of Mumbai slums and non-slums (Malani et al. 2020b), the study of urban and rural Karnataka (Mohanan et al. 2021), a follow-up study in the slums and non-slums of Bengaluru (where data analysis is ongoing), and four rounds of district-wise surveys in Tamil Nadu (Selvavinayagam et al. 2021).[11] The total sample size across these surveys was roughly 110,000 persons, representative of a population of nearly 170 million persons.[12]

11. In addition, I have provided advice to several other States that conducted and analyzed their own sero-surveys.

12. The total is 380 million if one counts populations surveyed multiple times.

These surveys yielded four important lessons. First, serological surveys are relatively inexpensive and quick. The Mumbai and Karnataka surveys each cost roughly INR one crore (ignoring the cost of the leadership team). The Mumbai survey took about two weeks to complete surveillance and two weeks to conduct data work. The Karnataka study took two-and-a-half months, but that is because we had a smaller team that visiting districts serially. In contrast, Tamil Nadu completed some rounds of its survey in two weeks because it employed government infrastructure and workers, and operated in 38 districts in parallel.

Second, the pandemic spread quickly and to a greater level than expected given the lockdown and antigenic testing results. The Mumbai serological study suggested that over half of slums were infected by July. This result was validated by surveys in other slums, even in other countries such as Bangladesh. Our Karnataka sero-survey suggested that 46 percent of Karnataka had COVID antibodies by August. All this was despite the lockdown and before the first wave peaked according to antigenic testing.

A corollary is that the government's initial pronouncements about the lack of community spread were incorrect. Either the government's testing strategy did not allow it to see that or its efforts to stem panic ended up reducing the credibility of government messaging.

Third, the only regular predictor of infection rates is population density. The Mumbai, Karnataka, and Tamil Nadu surveys did not reveal consistent differences in rates of infection by age or sex. However, they did reveal that slums had more infections than non-slums and that urban areas had more infections than rural areas. (Those gaps shrunk over time, as several waves of infection eventually did hit even less dense areas.)

Fourth, serological surveys measure past infection only before vaccination campaigns. Both prior infection and vaccination generate antibodies detected by serological tests. If the purpose of such testing is to measure the rate at which infection spreads prior to vaccination, to assess the risk from existing infrastructure and population mixing patterns, then vaccination confounds estimates of that risk. For example, between the third (June 2021) and fourth (December 2021) rounds of the Tamil Nadu survey, seropositivity increased by 23 percent, but 65 percent of the increase was due to the State's vaccination campaign rather than new infections. In contrast, 100 percent of round 1 (November 2020) and nearly all of round 2 (April 2021) seropositivity were attributable to infections (Selvavinayagam et al. 2021).

Fifth, antibodies are a medium-run measure of immunity. The metabolic (caloric) cost of mounting an immune response, including antibody production, is large (Demas et al. 1997). The body stops producing and slowly begins clearing antibodies after an infection is cleared. As a result, antibodies decline. Nevertheless, the body retains cellular memory (via T and B cells) of an infection that enables it to spin up antibodies more quickly the next time it is infected, reducing the burden from that infection.[13] Thus, in the absence of repeated reinfection or boosters, serological studies may underestimate population-level immunity. For example, between round 1 (November 2020) and round 2 (April 2021) of the Tamil Nadu surveys, seroprevalence fell from 31.5 percent to 22.9 percent. Certainly, neither the amount of prior infection nor cellular immunity declined in that short period.

5.1.5. Reforms

Experience with serological testing suggests several reforms to prepare for the next pandemic.

First, the government should embrace serological testing earlier in a pandemic. It should not make assumptions about whether a disease is symptomatic or not and let testing decide that. Moreover, it should appreciate that serological testing can inform population immunity better than antigenic testing, especially if the latter is limited and not conducted repeatedly on representative populations.

Second, the government should eliminate barriers to both antigenic and serological tests, especially when those are employed for population-level surveillance as opposed to individual-level diagnostics for purposes of quarantine and treatment. This means that whatever agency regulates testing should accept tests approved by foreign regulators that are reliable, such as the US Food and Drug Administration or the European Medicines Agency. Moreover, the government should automatically suspend tariffs on tests and testing materials once a pandemic is declared and there are inadequate domestic producers of tests. Finally, the drug regulator should also encourage private labs to apply for the BSL certification required to test for pandemic diseases, and expeditiously process those applications before the next pandemic. The regulator should not impose unnecessary safety requirements, but rigorously enforce those that are required to avoid infection of lab personnel and shutdown of labs.

Before implementing these reforms, the government should carefully consider which agency should regulate testing and which should conduct central government surveillance and research. It may be too much to ask one agency to do all these tasks. Moreover, government researchers may overweight their own research, generating conflicts of interest that make impartial regulation of other people's research more difficult.

Third, the government should expedite the implementation of population-level surveillance. It should prepare representative samples for testing. The Census Division of the Home Ministry and the National Statistical Office are

13. In theory, having a high antibody count when re-infected will reduce the health consequences of that re-infection more than merely having cellular memory because cellular immunity has a recall period that slows antibody response. The magnitude of this recall period, which is still being investigated, appears to fall with vaccine boosters (Wragg et al. 2022).

in a good position to do this because they conduct several surveys that entail generating censuses. The government may also want to maintain a stockpile of consumables such as plates and reagents, though the price of stockpiling rises if these are not durable inputs.

5.2. Measuring Mortality

Background. A central question in the pandemic is the probability of death, given infection (i.e., Infection Fatality Rate or IFR) and the total mortality burden.

While the infection has a substantial morbidity burden, that is difficult to measure. It is well accepted that COVID has a short-lived morbidity burden on those with symptomatic infection. Long COVID, which may last for months, if not years, is still being investigated.

Information on mortality is important for two reasons. First, to the extent that cases are not well counted, perhaps because of a shortage of supply or demand for tests, deaths are an indirect measure of both flow and stock of infection. Second, the ratio of death to cases provides a measure of the impact of infection. The greater the IFR, the more important it is to avoid infection.

Initially, the infection fatality rate was measured by dividing the number officially reported deaths by officially reported cases. The problem is that this might overestimate death rates. The government was only testing mainly symptomatic cases, and only a fraction of even those. This undercount would deflate the denominator of IFR.[14]

A solution was to replace the denominator with seroprevalence times population. This would capture all cases in the denominator. But this correct led to extremely low estimates of infection fatality rates, with India having perhaps one-tenth the estimated IFR of the US. Although some people proposed theories for why India might face a lower mortality burden,[15] others quite reasonably questioned India's estimate of COVID deaths (Cai et al. 2021; Levin et al. 2022). The same shortage of tests that plagued case counts might also affect death counts. Indeed, the value of testing a dead person not tested for COVID when alive has zero diagnostic value, which drove testing priorities. Finally, there may have been political pressure not to test dead bodies for COVID to avoid either panic or criticism of government COVID policy.

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14. Another, more technical problem is that the numerator and denominator can be measured as stocks or flows. Taking the stock of deaths and dividing by the stock of cases is fine if the IFR remains constant over time. But improved medical care might cause the ratio of stock values to overestimate the IFR. The alternative, taking the ratio of flows, say over a week or month, can yield errors unless one knows the right lag between detection of cases and detection of deaths.

15. Several theories were proposed, including cross-protection from prior BCG vaccination, to beneficial genetic mutations, to survivorship bias. This last explanation was that India had fewer individuals who would be most vulnerable to COVID, e.g., the elderly and those with co-morbidities, because many had already died from age and co-morbidities before the pandemic.

The next correction was to replace official counts of death with estimates of excess all-cause mortality. Data on all-cause deaths were obtained from States that had disclosed deaths reported to their Civil Registration System or deaths incidentally reported among the representative sample of another survey, such as the CPHS (Malani and Ramachandran 2021; Anand et al. 2021; Jha et al. 2022). Data journalists such as Rukmini S. should also be credited for this important work (Rukmini 2021). These all-cause death numbers suggested roughly 5 million or more deaths from COVID through 2021, roughly five times the officially reported estimates of COVID deaths. These excess death estimates, consistent with Chinmay Tumbe's warning about past pandemics, suggested that India had the world's greatest burden from death. (To be fair, Levin et al. (2021) suggest that all developing countries suffered mortality rates double that of developed countries, not just India.)

But all-cause deaths have three weaknesses. First, they are highly sensitive to how one computes counterfactual all-cause mortality rates in the absence of the pandemic (Malani and Ramachandran 2021). Second, excess deaths might include both deaths directly caused by COVID and those indirectly caused by the pandemic. For example, the pandemic or the policy response to it may have caused people to drive less and have fewer accidents or to avoid non-COVID care, raising mortality. Third and relatedly, it is difficult to convert all-cause mortality into an IFR number because it may include indirect causes of death. IFR numbers are based only on deaths among individuals infected with COVID and caused by that COVID infection.

One solution to this problem is to attempt to identify COVID-specific deaths without relying on official numbers. For example, Jha et al. (2022) conducted a survey that asked households to self-report COVID and non-COVID cases, as medically certified COVID deaths are rare. While the results of this study accord with those from excess death studies, one concern is that COVID deaths were self-reported. To improve these estimates. Jha and I teamed up with CMIE to conduct verbal autopsies on deaths reported in the CPHS since 2018. Verbal autopsies use a WHO-validated interview of next of kin that is then mapped onto ICD10 diagnostic codes by specially trained doctors. Our analysis will be out soon.

Reforms. India's whiplashed experience with measuring mortality highlights the need for better mortality tracking infrastructure. First, India should make public data in death registries from all States regularly and with less delay. India provides a national estimate of deaths using the Sample Registration System, which measures births and deaths in a representative sample of roughly 830,000 persons. However, that is usually reported after a two-year delay, much too late to be useful for policymaking. India should also encourage private efforts, such as by CMIE, to measure death rates, especially if private organizations can produce data more quickly than the government.

Second, India should consider conducting autopsies on a random sub-sample of registered deaths or conducting regular verbal autopsies on a sub-sample of reported deaths. While this is not a census of deaths, its smaller sample size might make measuring the cause of deaths and quicker reporting feasible.

5.3. Economic Recovery

Background. Data from the CPHS suggests that the economic cost of the pandemic was far less severe than that of the lockdown. As we noted earlier, poverty was somewhat elevated in rural areas, but inequality declined, relative to pre-pandemic levels. The data allow us to both see how households were able to protect themselves and why inequality declined.

In the immediate aftermath of the lockdown, households took two steps to protect themselves from the shock of the lockdown. First, they tried to recover income by shifting to a different occupation, usually agriculture (Gupta et al. 2021a). This was not their only response: reservation wages fell, suggesting that workers increased supply. The problem was that, outside of agriculture, demand fell so much that the equilibrium quantity of employment fell outside agriculture.

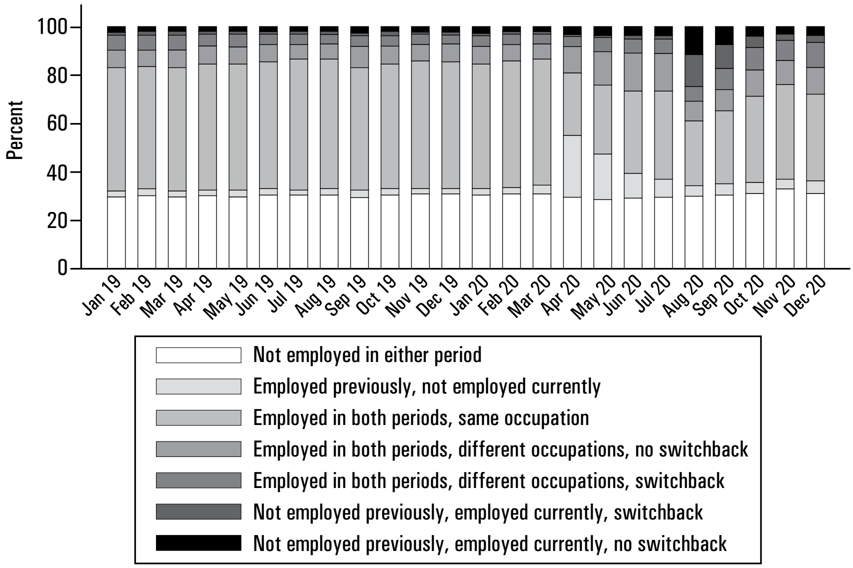
In the short run, this occupational churn was protective of income. Agriculture was the safety net for the COVID-induced post-lockdown shock to manufacturing and services. However, from the perspective of agriculture, it meant that a relative shock to another sector was transmitted to this sector. This ripple effect through labor markets means it is hard to confine shocks to a sector.

The long-run impacts of occupation churn are similarly uncertain. The shift to agriculture was temporary for about half of the shifting workers (Figure 10). Half switched back to their original sectors by the end of 2020. For those who remained in agriculture, the switch could be viewed as a long-term improvement. Frictions and risk discourage people from trying other occupations to which they might be better matched. COVID may have provided a shock that facilitated experimentation. Those that remained might be better off in their new sector. That said, the larger labor supply in agriculture might suppress wages in that sector. Moreover, development is usually associated with a shrinking agricultural sector, not a growing one.

The second step that households took to protect themselves was to use formal and informal credit and informal insurance to smooth consumption, as they did before the pandemic, and to prioritize food and fuel consumption. Households used these adaptations less than during the lockdown, but they persisted through September 2020.

An interesting feature of India's economic performance post-lockdown is that economic costs did not spike as cases did. In fact, income and consumption rose even as cases rose and peaked during India's first wave in September to

FIGURE 10. Labor Force Status over Time



Source and Notes: This figure and note are taken from Figure 8 of (Gupta et al. 2021a). This figure was constructed by, first, categorizing each member of each household into five States in each month they are observed: not employed now and in the last period, not employed now but employed last period, employed in same occupational category as the last period, employed in a different occupational category in the last period, employed but unemployed or OLF in the last period. (We define not employed as out of the labor force (OLF) or unemployed, categories found in the CPHS data set. The last period is defined as 4 months ago, which is the last time the member was surveyed in the CPHS.) We then calculate the fraction of the observed members in each State in each month. The figure includes only those members aged 18-65 years. Switchbacks are measured by examining whether the individuals switch to a sector they had previously worked in either four months or one year previously.

October 2020. This contrasts with the second wave in May 2021, during which income and consumption fell at the same time as cases and deaths peaked.

An explanation for the different economic effects of the first and second wave is the differential timing of policy response (Figure 5). In 2020, the lockdown was implemented, and mobility declined, well before the first wave. This declining mobility is a correlate of income and consumption. In 2021, however, the government did not implement local lockdowns until the second wave had arrived, that is, when mobility fell, along with income and consumption. (An argument could even be made that voluntary distancing, also reflected in mobility, declined before the government tightened suppression policy.) It is possible that wave 2 offers a counterfactual of what might have happened in 2020 if the government had not declared a lockdown in anticipation of cases.

Examining the mechanisms for why poverty returned almost to pre-pandemic levels and inequality actually fell relative to pre-pandemic levels reveals some important economic dynamics of a pandemic. Gupta et al. (2021b) suggest two explanations for why poverty and inequality declined during the bulk of the pandemic.

First, incomes of the top quartile households (the "rich") depend more on business income (Figure 8) and business income is more sensitive to aggregate shocks. This is consistent with data from the US, which also finds that the incomes of the rich have greater "beta" (Guvenen et al. 2017). Second, the demand for services, which involved interpersonal contact and infection, fell more than the demand for manufacturing and agriculture, and the rich are more dependent on labor income from services than are the poor (Figure 11).

Almost as important as the mechanisms by which the pandemic affected poverty and inequality are the mechanisms by which it did not do so. Gupta et al. (2021b) suggest that government transfers, cash or in-kind, did rise during the pandemic, but played a small part in income dynamics (Table 2). Moreover, labor supply did not contract, despite the risk that working could lead to infection.

TABLE 2. Attribution of Changes in Inequality during the Pandemic to Different Components of Household Income

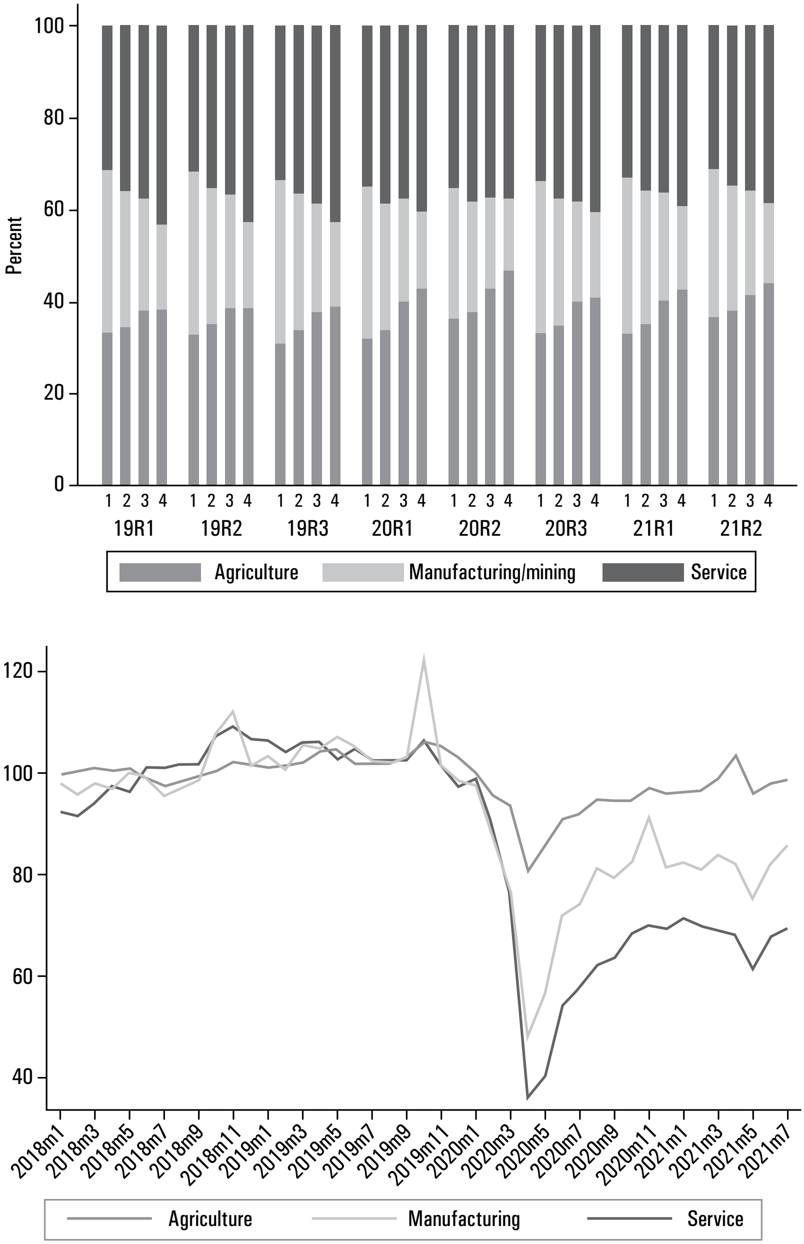
Components of income	*Change in inequality due to*	
	Change in share of income from component	*Change in amount of income from component*
Total income		-39.74
Labor income	5.41	-24.93
Transfer income	0.18	-0.33
Other income	-2.03	-1.97
Business income	-6.70	-9.38

Source and Note: Table and note is copied from Malani et al. (2022). Changes are from 2019 average to July 2021. Units are percentage points. Data is from the Consumer Pyramids Household Survey.

Reforms. Economic surveillance after the lockdown suggests economic reforms to prepare for the next pandemic. First, the government should consider conducting a CPHS-like survey that follows families over time. It can either borrow CPHS's strategy of a fixed but growing sample or mimic the Current Population Survey in the US, which rotates new households in every year, with households remaining in the sample for a fixed number of periods. It would be good to have a second data set to validate the lessons of the CPHS, especially given concerns about CPHS sampling strategy.

Second, until the Indian government has substantially greater fiscal and administrative capacity, it is unlikely that government transfers can or will play as big a role as self-protection to help the poor. This is not necessarily a bad thing: the US expanded money supply to stimulate the economy with transfers and, while successful at alleviating poverty, it may be partly responsible for the

FIGURE 11. Income by Sector and Quartile and Consumption by Sector, Over Time



Source and Notes: Figure and note copied from Figure 5 in (Gupta et al. 2021b). Left panel: Each bar reports the share of the population in each quartile with occupations in each of the three sectors (agriculture, manufacturing, and services) in each month. Right panel: This plot shows aggregate consumption of goods in three sectors by month relative to aggregate consumption in that sector in 2018.

current spike in inflation. India had a far smaller stimulus, and the poor still survived the pandemic.

Third, labor churn is an important safety valve and the government should eliminate barriers to migration and occupational change. In this crisis, the risk was from infectious disease. If in a future crisis, risk came from husbandry or blight, non-agricultural sectors may serve the cushioning role that agriculture played during COVID. To maximize the ability to adapt, the government should limit occupational licensing and regulatory hurdles to new business formation. (These reforms had value before as methods to reduce informality in the economy. Now they also serve a role in facilitation adaptation to shocks.)

6. Conclusion

Learning the lessons in this paper would not be possible without a robust private sector, collaboration between the government and the private sector, and room for respectful disagreement and debate across sectors and disciplines. In the US, there was a glut of infectious disease experts, and they used their credentials to limit out-of-the-box thinking. Moreover, political polarization meant that dissent was disparaged as politics. India to some extent avoided these pitfalls. As it builds out capacity to fight the next epidemic, it should be careful to avoid excessive specialization and injecting politics into reasonable policy dialogues.

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To view the entire video of this IPF session and the General Discussion that ended the session, please scan this QR code or use the following URL
https://youtu.be/0BGmhY0tCTQ

Comments and Discussion*

Chair: **Surjit Bhalla**
IMF and NCAER

Shamika Ravi

ORF and Brookings Institution

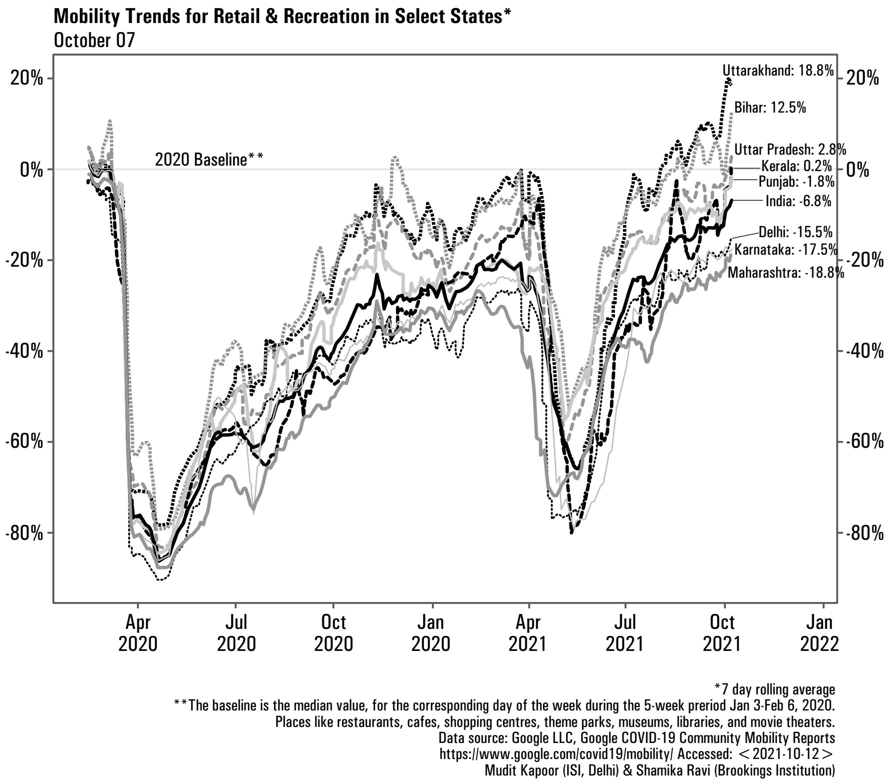
The author has written a comprehensive and exhaustive paper. He has conducted an extensive literature review but there are certain assertions which need to be addressed, and in hindsight highlight the difficulty in modeling and forecasting tail events. First is the question of how India could have detected the pandemic earlier, which is how the paper begins. The paper's assertion that India did not act until cases reached its shores needs to be questioned, in that at what level of cases did comparable countries react, in an attempt to understand what more could be done.

Next, I will be getting into specific policy initiatives such as travel restrictions and lockdowns. The paper claims that travel restrictions are of limited value in controlling epidemics and that quarantine deters testing. However, no specific evidence is provided for the same. There is also the question of how many reported cases should there be before countries announce lockdowns, and whether there was something such as optimal testing. The paper also claims that Consumer Pyramid Household Survey (CPHS) data shows that the mean and median incomes fell before the national lockdown. However, a series of steps were taken before the national lockdown. The lockdown was imposed several weeks after the Epidemics and Disease Act (EDA) was invoked across States, as well as after a series of travel restrictions were imposed. The author claims that the lockdown did not avoid infections, and in fact, it may have accelerated infections in cities. However, more research is needed on whether it was the lockdown itself that was accelerating infections or the density of the disease.

The modeling section is a good contribution to the paper. However, it exposes a gap related to human behavior, that is, the assumption that human behavior is unaffected by the occurrence of an epidemic. That this is a problematic assumption becomes clear from the Google mobility data shown in Figure 1. In

* To preserve the sense of the discussions at the India Policy Forum, these discussants' comments reflect the views expressed at the IPF and do not necessarily take into account revisions to the conference version of the paper in response to these and other comments in preparing the final, revised version published in this volume. The original conference version of the paper is available on NCAER's website at the links provided at the end of this section.

Figure 1. Google Mobility Data for States of India



the second wave of infections in India (the Delta wave), most States witnessed a dramatic decline in the mobility of people even without any lockdown impositions. In places where lockdowns were imposed, these were announced weeks after a significant decline in the movement of people. This shows that people's behaviors do, in fact, change according to the spread of the infection. For epidemiological models to assume otherwise is a major shortcoming of these models and the likely explanation for why the predictions were repeatedly wrong.[1]

1. "India's COVID-19 'human barricade' to keep cases under control" say experts – Reuters, 17 February 2021 (just weeks before the deadly second wave in India): https://www.reuters.com/article/health-coronavirus-india-idUSKBN2AH1K7

Trying to model tail events is not an easy feat, as depicted in various forecasts and predictions that were put forward and made publicly available to people. When modeling future events, the weights are very low, so using past data to predict the future is hugely problematic. Models may be over fitting data, which makes predictions problematic, especially considering the sparse availability of data. Unlike the predictions of epidemiological models, which were repeatedly proven wrong, we were closely scrutinizing the actual data on the ground. A simple moving average (7 days, 10 days) of actives cases, confirmed cases at the disaggregated level (States, districts) gave us much better information of the situation,[2] and was instrumental in shaping policy responses.

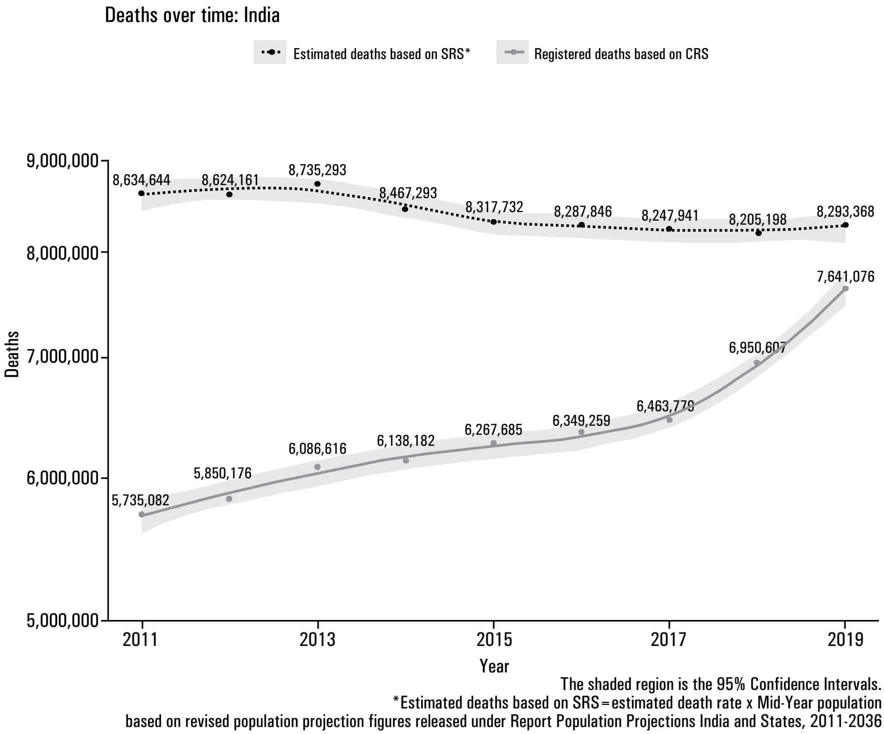
The part about estimation of excess deaths is slightly messy, as the structuring of data in India is such that makes estimating such a variable very difficult. Local area estimation makes proportionality assumptions in States where data is not available and that is a problem. Migration creates further problems as the proportionality that is being assumed does not remain stable over time. There are other concerns as well. For the WHO study, modelers have admitted errors; for example, in Germany, their model was sensitive to the spline function being used to make counter factual calculations. However, Germany is an OECD country with a robust CRV system, unlike India which makes a lot of guesstimates. The standard errors for India estimates were revised at least three times. Hence, models need to be scrutinized for their assumptions. The number of registered deaths in India has been on a rise, but the number of estimated deaths has remained somewhat stable. The ratio of registered deaths to the estimated number of deaths varies a great deal across the Indian States, due to a systematic bias in big cities that have healthcare. This strengthens the case for the proportionality assumption being hugely problematic.

However, a thorough analysis of the death data from the Civil Registration System (CRS) has frequently shown grave flaws.

This suggests that mortality data from the CRS is not a trustworthy source of death until adjustments are done for sex, age, and location, which is largely to establish the baseline estimates before the pandemic compared with registered death data during the epidemic. Reiterating that in 2019, the CRS reported registering 7.64 million deaths overall, or 92 percent of the total fatalities estimated by the Sample Registration System (SRS) is crucial, as shown below in Figure 2.

2. "Five points about the second wave" – Business Standard https://www.business-standard.com/article/opinion/five-points-about-the-second-wave-121050701470_1.html.

Figure 2. Estimated Deaths and Registered Deaths in India



Source: Author's estimation.

However, the total number of deaths in 2019 was 9.92 million when age, gender, and location adjustments were performed. After accounting for age, sex, and location, the overall level of registration (LOR), or completeness of death data, was therefore 77 percent, which was 15 percent higher than the previous year. Researchers C. Rao et al., for instance, demonstrated that the CRS data on deaths (7.64 million) undercounted the number of deaths by 2.28 million for 2019 (prior to the pandemic). This undercounting was systematically worse for the elderly (over 60 years old) and children (under five years old), who accounted for 56 percent and 30 percent, respectively, of the additional deaths. They also discovered, not surprisingly, that changes in the States of Bihar, Jharkhand, Madhya Pradesh, Maharashtra, Rajasthan, and Uttar Pradesh were responsible for 75 percent of the extra deaths.

The household survey, such as the C-Voter tracking survey, is another data source that academics have used to calculate the number of extra fatalities. It is a daily nationwide poll that uses computer-assisted telephone interviews, though its main objective is to monitor how people perceive the government, the media, and other social indices. The sampling strategy and the questionnaire were not meant to gather information on household deaths. In India, the Sample Registration System (SRS), a comprehensive demographic census, provides a trustworthy source of death statistics. Over 8 million individuals in all States and Union Territories are covered by it. Its main objective is to generate national and State-level birth and mortality rates. Unfortunately, the pandemic prevented the SRS survey from being completed. In comparison, the C-Voter tracker survey is a crude and inaccurate way for gathering data on deaths, with a coverage of 0.14 million adults and death counts relying on self-reported data from telephonic surveys without on-field verification. Furthermore, the low response rate raises important questions about non-response bias that are difficult to quantify.

Researchers made the assumption that respondents' responses to survey questions would not vary over time. Instead, increased media attention, general concern, and interest levels during the pandemic waves would suggest the potential of a range of reactions from the populace. For instance, during a wave, people would be far more attentive to the surroundings and occurrences than they are at other times. The estimates of excess deaths are seriously questioned because of these naive assumptions.

Due to the lack of precise fatality statistics, there has been a lot of political speculation. The fact is that India lacked a system for gathering accurate, real-time statistics on deaths even before the pandemic. No matter how sophisticated the statistical methodology, there is still no alternative for excellent quality data, which is the real problem, not whether the statistics are correct or incorrect. The rate of death registration in India increased significantly from 75.3 to 92 percent between 2015 and 2019 as a result of significant efforts to digitize the country. However, there are still a number of issues with this work in progress, including the startling 2.28 million deaths(or roughly 23 percent of all deaths) that were not included in the CRS mortality data even in 2019. With low levels of registrations, the situation was exponentially worse.

Overall, this is a very comprehensive paper, but for policy-makers to take it seriously, we will have to get down to the dirty details of data and the data systems that exist in India.

Sonalde Desai

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West Wing, a TV Serial about a Nobel prize-winning Economist who becomes the president of the United States, has a line, "Economists were put on earth to make astrologers look good." We need to rephrase it to say that, "Epidemiologists were put on earth to make economists look good."

Predictions in response to COVID-19 do not cover any segment of the research community with glory. We have been remarkably wrong in so many things! This paper does an excellent job of outlining some of these bloopers. Let me highlight the key findings and connect them to some additional observations:

1. When the United States failed to close its borders to its citizens returning from Chinese New Year celebrations in Wuhan, resulting in a rapid spread of SARS-CoV-2 in the US, the world took a lesson that closing down borders will stop the virus at our doors. Nonetheless, India's sharp clampdown around its borders did not stop the virus from entering India. The disease had already spread by the time travel restrictions were put in place.
2. The author, Anup Malani, notes that, perversely, the lockdown allowed the virus to breed within densely populated urban slums, leading to an extremely high infection rate.
3. The *mantra* of "Test, Trace, Track" that the international community repeated was ineffective because many infected individuals were asymptomatic and could not be identified. While there is some hope that governments can track and quarantine symptomatic individuals and their known contacts, asymptomatic individuals continue to spread the virus. Quarantining, of course, has the perverse effect of reducing the willingness to be tested. The author asks us to focus on super-spreaders, but how can we identify these people? Moreover, "super-spreader" is not a politically innocuous term. In the US, it applied to Chinese immigrants, and in India, to Muslims initially following the Tablighi Jamat incident. In both cases, it led to substantial discrimination.
4. Disease modelling had some success in the short run, but in the long run, it was ineffective because the data needed for robust modeling were not readily available. Moreover, as the author notes, political sensitivities and interference made it difficult to develop good forecasting for effective policy development. Hence, we continued to operate in the dark, toying with full lockdowns, limited lockdowns, and containment zones.

The lesson suggested in the paper is that we need better data, more timely data, more diverse data, and more sophisticated, homegrown modeling. This is a very thoughtful and practical paper in which the author makes several recommendations, which I want to group into four as follows:

1. The forecasting models need to improve.
2. To do that, we need better data. We should encourage the collection of better data from individuals and governments. The author mentions some interesting data collection efforts that he has been involved in, such as

testing for seroprevalence. He also notes that we should increase the incentives for individuals to get tested so that our COVID prevalence data is based on a representative sample and not on sick individuals.

3. We need the government to stop being secretive and controlling, and let diverse groups work, let the data be publicly available, and trust the public not to create a panic.
4. We should link economic data to disease surveillance.

If I were to lay out a future research agenda, I cannot imagine doing a better job. He covers diverse terrain, except perhaps collection of behavioral data that would facilitate agent-based modeling, so we don't just have to rely on SIR models or their variants. But much as my researcher's heart palpitates at these exciting opportunities, I am not sure that we are offering policymakers sufficient guidance on preparing for another pandemic, even when it comes to the data they need to make decisions.

Almost certainly, the R_0 for any new virus will be different; it will affect other sections of the population, and antibodies may last longer or shorter than SARS-CoV-2. It may or may not mutate as quickly as SARS-CoV-2 has done. Fatality caused by that virus may be higher or lower. So, future policymakers will benefit as much from our current experience as we did from the Spanish Flu of 1918.

Even research based on the author's favored method, that is, seroprevalence studies, highlights the limited predictive power of these studies between the Alpha and the Delta waves, as the virus continued to mutate.

The following two examples are illustrative:

1. A seroprevalence study of approximately 28,000 participants selected from 274 wards in Delhi was carried out in January 2021 (Sharma et al. 2021). The sample was selected using a systematic multi-stage sampling procedure that should allow for a random example of people ages five and above in the Delhi area. Venous blood samples were collected and transported to a lab to be analyzed using the VITROS® (Ortho Clinical Diagnostics, Raritan, NJ, USA) assay (90 percent sensitivity, 100 percent specificity). Seroprevalence of Anti-SARS-CoV-2 antibodies was about 50 percent for the population and 56 percent after adjustment assay characteristics. Antibodies were detected in almost all sections of the society, including the young, old, male, female, and slum-non-slums. In the light of this implied widespread immunity, the sharp spread of the COVID-19 Delta variant and the concomitantly high death toll barely three months after this study comes as a surprise.
2. One might say that 50 percent does not signify herd immunity yet. But a study from Manaus in Brazil (Sabino et al. 2021) published in *The Lancet* found that even a seroprevalence of 76 percent in October 2020 was

insufficient to protect the population from the Delta wave by March 2021. This may be because the immunity may have waned quickly or because the Delta variant was able to evade immunity generated by a previous infection.

Whatever the reason, we know now that despite very high levels of seropositivity, most populations worldwide, particularly in India, succumbed to the Delta variant of COVID-19 with tragic consequences.

So, what is a policymaker supposed to do?

Although we hope and pray that this was a once-in-a-lifetime event, we do not need to be Bill Gates to believe that a recurrence of a similar or even more virulent pandemic is possible and that lightning could strike twice. Moreover, pandemics are not the only emergencies nations face. Some of the discussion below also applies to other catastrophes such as earthquakes, floods, and other calamities that bring their own destruction of lives and livelihoods.

Instead of turning the present experience into advocacy for more and better data for the same kind of modeling, let us start from a clean slate and develop some governing principles for future policymakers and then ensure we have sufficient data to support these decisions.

1. **Early warning of potential threat and severity of this threat will be helpful.** Unless the virus originates within our national boundaries, we will need international collaboration to get an early warning about the emergence of a new virus, its characteristics, and the severity of its impact. India should use its Presidency of G-20 to lobby for an international network and protocol for data-sharing that does not rely on WHO but where scientists can talk to each other. We also need to give up our faith in Indian exceptionalism and assume that unless proven otherwise, any disease that strikes Sweden or Uganda will have similar features if and when and it reaches India. A good example is how relying on the UK experience allowed India to spread vaccination and vaccinate a large proportion of the population during a vaccine shortage.
2. **Move from a singular focus on prevention to management.** Our COVID-19 prevention strategies were rooted in our experience with HIV/AIDS. The only way to prevent the spread of HIV is to undertake behavioral change. But COVID-19 spread through the air, not through specific contacts like sexual relations or needle exchange. Density makes it challenging to prevent impersonal communication. Hence, instead of putting all our eggs into the prevention basket for a future pandemic of an unknown nature, we should also figure out how we will manage the symptoms and reduce long-term complications. From a data perspective, developing a management system that identifies trained personnel and equipment such as ventilators and cold boxes will help mobilize a quick response. The present pandemic has helped us create a variety of

management systems. Building on these to track inventory and trained personnel would help address future emergencies.

3. **Develop processes for delivering welfare benefits quickly.** During emergencies, delivering welfare is difficult. Hence, we often end up providing benefits to people who are part of our system, regardless of whether they are the neediest ones or not. The Indian Government sent out advance payment of PM-KISAN, transfers into the Jan Dhan account, and additional rations. All are very welcome. However, as the plight of migrants walking back to their hometowns showed, they were not part of the system through which they could receive these benefits. Many did not have ration cards, and hence could not get extra rations. Our method of delivering benefits was akin to looking for the key under a light pole rather than where it was lost because we had to rely on existing registration systems. This experience shows the importance of developing a comprehensive, location-linked social registry that could be quickly activated to provide benefits to the targeted beneficiaries, be they in cash or kind. Given the privacy concerns, this registry will need to be voluntary.
4. **Develop a sophisticated decision matrix for identifying the potential risks and benefits of a lockdown.** Early epidemiological models from institutions like the Imperial College and Institute for Health Metrics and Evaluation (IHME) generated a sense of emergency that led governments to implement severe lockdowns in many cases. However, the lockdown is a blunt instrument that can be used in the short run to prepare for a better response to upcoming emergencies. Still, its indefinite continuation creates a very different crisis. School closure provides an exciting example. Arguably the most significant long-term consequences of the pandemic will come from learning losses associated with school closures. Even after travel was allowed, lockdowns were eased, and economic activities resumed, schools remained closed. India has some of the most extended school closures worldwide and even in South Asia.

We need to know whether these school closures were justified from a health perspective before trying to balance health risks against learning losses. Understanding the disease consequences of various school closure policies may be worthwhile. Research on Sweden offers an exciting example. At the onset of the pandemic, Swedish upper-secondary schools moved to online instruction, while lower-secondary schools remained open. This allows for a comparison of parents and teachers differently exposed to open and closed schools but otherwise facing similar conditions. A careful analysis by Swedish economists published in PANAS (Vlachos et al. 2021) shows that parents matched on everything except having children in lower secondary versus upper secondary schools show similar levels of PCR-confirmed infections. Perhaps the virus carried by their children was not their only source of infection. The study did not include tests on children. Still, given the correlation of infectivity within families, there is a good chance that parental infection is a good proxy for child infection. Teachers in lower secondary schools who delivered in-person instruction were more likely to be infected than teachers in upper-secondary schools. However, school closures were mandated on the grounds of student health rather than teacher health since teachers are often counted as essential personnel, and teacher health would need to be treated in the context of other high-risk occupations such as grocery store clerks, bus drivers, and Amazon delivery personnel. Whose health concerns should dominate decisions regarding school closures? These are the questions worth exploring in developing a pandemic preparedness plan.

I want to end by acknowledging the enormous uncertainties under which policymakers operated throughout the pandemic. No one knew what we were dealing with at the start of the pandemic. We did not know how rapidly COVID-19 would spread, how virulent it would be, how successfully we would develop vaccines, and how best to produce and administer the vaccines. Operating in the dark, the nation and its leaders did their best. The Government recognized the seriousness of the pandemic and tried to act swiftly; the population rallied around the need for harsh lockdowns. NCAER's studies in Delhi showed that in April 2020, nearly 85 percent of the respondents supported the lockdown, and 66 percent continue to believe even after a year and a half of its imposition that it was the right decision. Individuals modified their behaviors and voluntarily tried to reduce social contacts, even in crowded slums where this is difficult.

Most importantly, vaccine development, production, and delivery have been remarkably successful, and India can take justifiable pride in this achievement. However, we also saw some tragic consequences caused by the lack of hospital facilities and ventilators. The social and economic impact was severe to begin with, and may have long-term effects for learning losses. Treatment sometimes brought other complications, such as steroids leading to black fungus.

Thus, a discussion like this is vital in preparing for future pandemics and other calamities. I congratulate the author, Professor Anup Malani for his thoughtful reflections on this paper.

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General Discussion

The Chair, Surjit Bhalla, commended the fascinating and valuable paper and said that it raised a critical research question: What data do we act on? Obviously when the COVID-19 pandemic hit, everybody wanted information, but there were no data except on the plague in the past, which of course, was vastly different. Some of the papers cited clearly needed further research. He urged the research community to be more diligent while conducting their research on such issues to prevent skepticism about their findings among the public. It is also important to act on all the available information to avoid paralysis on action. One of the suggestions the paper made is to further research, as the big payoff for research is that we can get to the action faster. But we should refrain from criticizing the authorities as they were doing the best they could based on limited knowledge. As regards the author's suggestion on the need to attain more collaborative data, the World Health Organization (WHO) was already doing that efficiently.

Ruchir Agarwal raised some important policy points and issues for the research agenda, as the head of the IMF's Pandemic Response Task Force. The first was a backward-looking point. During the peak of the Delta wave of the pandemic, the number of cases in India was 400,000, as on 7 May 2022. However, cases were already rapidly rising in Maharashtra about 4 to 6 weeks before that. He suggested that it would be a great case study to bring together academics and government officials to understand what did not work well and how things can be done better the next time. That agenda does not require modeling, it just requires more effective coordination across States. The forward-looking points are as follows: First, COVID is going to be with us forever, and its impact in India will continue in future. Just as Dr Sonalde Desai talked about the long-term effect of school closure during the lockdown, he also flagged the effects of long COVID, especially its long-term effects on health.

Second, COVID will not be the last pandemic. So, this is an opportunity for us to build a health-strengthening system agenda at the local level that is coordinated at the national level, based on the lessons learnt during the COVID pandemic, such that when the next pandemic happens, regardless of the nature of the pathogen, we can handle it better based on the lessons learnt during COVID and hand over that knowledge to the next generation.

Devesh Kapur pointed out that in 2021, the Supreme Court had announced that everyone who died of COVID would get a cash payment. He asked if anyone had looked at the data on how many people had made claims to get this money, as such claimants would have to give details on deaths, and that could be an alternative or additional source of data, as clearly there is an incentive for people to claim the money. He also asserted that whenever there is an occurrence like COVID, the main attention is on the national government. But public health is constitutionally a State subject. So, what did this tell us about how much States prioritize public health? One way to address this issue is to examine the State budgets in the most recent year and look for any differences in public health spending.

Shamika Ravi averred that she could speak for one State, Madhya Pradesh, because she was working with them. She revealed that the State had recorded a 35 percent increase in the health budget in the last two years, which is almost entirely because of the pandemic. Although Madhya Pradesh is a poor State and amongst the bottom four in terms of per capita income, it was surprisingly in the top four when it came to the vaccination drive. This indicates that the State government has realized that they have the means, or at least the governance architecture, through which they can get some basics right. There is a task force which is monitoring data on the neonatal mortality, infant mortality, and maternal mortality, largely looking at maternal and child health, and that whole initiative has ostensibly happened thanks to the pandemic. There is also a growing awareness about the need for ensuring such interventions in the health sector. The second issue pertains to the Ayushman Bharat scheme, on which the National Health Agency (NHA) has data. It is not really driven by the Supreme Court ruling. The Government may contest that ruling, as it has huge fiscal implications, but the data with the NHA will be able to show if it is an alternate and efficient way to measure the death numbers. There is also an incisive paper from the Insurance Regulatory Development Authority (IRDA), which looks at insurance claims around this time. She also remarked that the C-voter survey basically assumes that the compliance or the response rate in the survey is going to be the same in the middle of the Delta wave as it was before. This survey therefore leads to biased estimates.

Mridul Saggar wanted to know how exactly the author was measuring the lockdowns, in terms of the database used and the availability of other databases. He said that researchers were mostly using the Oxford Stringency Index, which is not a very reliable measure because it just takes the maximum restrictions in a particular city at a point of time. It virtually gives no idea and probably any research based on that would be completely misleading.

Ram Singh noted that the author was arguing against an official government monopoly over disease data and by implication, in favor of private ownership of the data. If the idea is to ensure that private entities own and use disease-related data in the presence of a lot of uncertainty about how data or any given data could be read and interpreted, it could make governments even less receptive to what one makes of that data.

Neeraj Kaushal stated that lockdowns would have different impacts, depending on whether they were imposed at the beginning of the pandemic or at a later stage during the pandemic. This is a highly endogenous and not an exogenous policy. The human and public policy response to it is not exogenous. So, some of our interpretations have to do with the way the policy has been implemented, depending on the kind of lockdowns. She asked if there should have been school lockdowns, and whether business lockdowns would have had a different kind of impact. Hence, any generalized statement about the impact of lockdowns in one particular country, and whether it would have the same kind of impact in another, is probably an exaggeration.

Arokiasamy Perianayagam commented on the discussion on counting excess mortality deaths of COVID. There are lot of estimates floating around. Different authors have proposed different estimates, and the number may be 4 million, or 5 million, or 3 million. According to WHO estimates, it is 3 million. The best way to get an answer to resolve this is to refer to SRS data. Say, the current count or pre-pandemic count is 8 million, we would have to wait for the next round of SRS data, and it could take another two years to get data for the period 2020-22. If the SRS data comes out with mortality estimates, then we will know the correct number of excess mortalities. The other option is that we have very good health survey platforms, such as the DHS, which is equivalent to the National Family Survey, India, and other health survey platforms like the one at the National Sample Survey Organization (NSSO). They do a highly robust sampling of methodology platforms, which can be used to do a quick survey, to add a component of mortality as a couple of retrospective questions on mortality in the last two years, and ask about the active component of the WHO verbal autopsy model, which has been implemented in many surveys. This sort of a scientific survey will provide a very reliable estimate of excess mortality, and demographers are adept at assessing these numbers on mortality and fatality. That is thus the best way for resolving the mortality data question.

Sonalde Desai responded to Ram Singh's comment on the debate on public data versus private data. She said that she is a big believer in private data collection and triangulating with public data, during the pandemic we are dealing with a very different situation. She pointed out many researchers had been doing telephone surveys at NCAER during the pandemic. It was very easy to do surveys during the first lockdown because nobody was sick. People were sitting at home, and were very willing to answer the questions. But NCAER researchers did not want to do the survey during the Delta wave because when people are under tremendous distress, that is not the point at which they would want some social scientist calling up to get the data. That also applies to a lot of issues associated with pandemic data. For instance, people who had a death in their household are not going to want to answer your questions, and researchers should not even be bothering them. We have to take our data collection tasks, private or public, with some level of humility, particularly during times of such an emergency.

Surjit Bhalla concluded the discussion by advising the research community to be humble because the real fact about the pandemic is that the whole class had failed and they are not willing to admit it. This includes all the major institutions in the world that are supposed to help public policy, including the WHO and the Center for Disease Prevention and Control (CDC). In December 2019, the CDC published research based on the last 70 years of pandemics, saying that masks and social distancing do not matter. There may not be evidence even now that these two things matter. But, there was a failure on the part of all the stakeholders.

As regards the suggestion on preparation for the next pandemic, economists certainly have to worry about the benefit cost of preparing for the next pandemic, and each country has to do the cost-benefit analysis. Given that a pandemic is a public bad and information flows very freely, why should India be investing in preparing for the next pandemic rather than improving its health care and taking care of non-pandemic related illnesses and deaths and diseases?

He also asserted that the pandemic had thrown up a critical and interesting finding. Developing countries, on average, have much worse health care systems. They are poor and are not so careful. Advanced countries are the most careful, have the best advance health systems, and the best economists and the best modelers. Yet, all the data, including the most robust statistics, show that developing nations had a much lower incidence of COVID-19 and much fewer deaths, even after accounting for the number of excess deaths, than their advanced counterparts. He said that he had asked this question to international organizations too—they do not have an answer or they do not care to answer. We also have to recognize that unfortunately, the pandemic led to extensive analyses, large-scale prescriptions of drugs, and a heavy dose of ideology and politics. In his opinion, this was because everyone was searching for answers to deal with one of the deadliest pandemics in human history, leading to massive tragedies around the world.

Lastly, he advised the author to highlight in the paper two major successes of the Indian Government, that is, its extensive COVID vaccination drive across the country, and its efforts to help migrant workers and the poor through various welfare schemes for food distribution and monetary support to alleviate the misery of poor households and enable them to tide over the livelihood crisis created by the pandemic.

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