

Mitigate/Suppress/Maintain: Local Targets for Victory Over COVID

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There is growing consensus around a strategy centered on testing, tracing, and supported isolation (TTSI) to suppress COVID, save lives, and safely reopen the economy. Given the high prevalence the disease has reached in many OECD countries, this requires the expansion of TTSI inputs to scales and with a speed that have little precedent ([Siddarth and Weyl, 2020](#)). AAs scarcity of testing supplies is expected to remain during the build-up to a surge, authorities will need to allocate these tests within and across localities to minimize loss of life. This paper documents a preliminary framework that aims to provide such guidance to multiscale geographies, in conjunction with our previous recommendations. Given unfortunate limits in current testing capacity, we describe a testing and tracing regime in which orders of magnitude fewer resources can be used to suppress the disease. Such suppression should be rapidly scaled in low-prevalence areas (within and across regions) to the extent that those areas can be insulated from other areas. In particular, if travel restrictions are used to allow asynchronous suppression, and if logistics permit the use of mobile resources, a smaller number of tests per day may be required. At the same time, vulnerable communities and essential workforces must be protected across regions, as prescribed in Phase I of the Roadmap to Pandemic Resilience ([Allen et al., 2020](#)).

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01 Estimates for Testing and Tracing

There is growing consensus that a strategy of testing, contact tracing, and supported isolation (TTSI) is a central plank of a strategy to suppress COVID-19 (C19) and save lives, while stably allowing the resumption of most economic and social activity. Many states have embraced such an approach ([Abbott, 2020](#)), the White House has extensively discussed it ([Hennigan, 2020](#)), and the presidential challenger has endorsed it ([Biden, 2020](#)). There is also growing consensus that success of such a strategy will require massively scaling-up testing to millions of PCR tests a day ([Siddarth and Weyl, 2020](#)) combined with contact tracing, which requires the hiring of hundreds of thousands of contact tracers ([Simmons-Duffin, 2020](#)).

Estimates of required testing and tracing capacity, however, are exceedingly coarse. There has been wide confusion about appropriate numerical targets, with estimates by the same individuals or entities changing by orders of magnitude literally from day to day. Furthermore, these aggregate estimates provide only limited guidance to more local jurisdictions on the testing and tracing levels they should target, or how presently severely limited testing capacity should be allocated within and across jurisdictions, to the extent that coordination is possible, as we ramp up to meet broad national needs. This paper attempts to fill this gap by both improving the precision of targets and disaggregating them across Metropolitan Statistical Areas (MSAs) and rural areas in states, and by analyzing how to allocate limited resources to protect the most lives. This should be viewed as a proof-of-concept, with greater disaggregation, more complete incorporation of other relevant factors, and more precise targeting needed in the future, based on the same principles.

The primary goal of this work is to provide a set of methods for policymakers. However, to illustrate our initial results, this paper highlights several striking qualitative findings from our analysis, and the following documents the methods behind our findings

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Estimates for Testing and Tracing

1. Data on confirmed caseloads and their associated required testing estimates are of little current value to policymakers. More reasonable estimates backed out of excess death statistics are typically five to ten times greater than confirmed case numbers. Additionally, confirmed case numbers are circularly driven by testing availability, whereas excess death estimates are less sensitive to variances in testing capacity. At the same time, figures on prevalence are highly dynamic as the disease spreads, and data on confirmed cases give a more up-to-date picture. We thus rely on a combination of these figures.

2. Suppression of the disease may be achieved with significantly fewer resources than previously estimated, with resources largely concentrated in an initial surge. Given limits on testing capacity, fewer tests may suffice to suppress the disease in many areas, based on the extent to which testing capacity is mobile and understanding that suppression may need to be sequenced rather than fully synchronized. Daily test capacity required for disease suppression estimates may be misleading from a disaggregated perspective because disease suppression requires a peak effort to suppress the disease and thus reduce the disease prevalence to which the TTSI strategy responds, followed by less intensive maintenance in low-prevalence areas. With appropriate methods, suppressing the disease may require little more than 100 million total tests, in contrast to the near 2 billion implied by projecting static per-day estimates based on peak periods over the full course of the pandemic.

3. In at-risk low-prevalence regions, it is possible to maintain disease suppression less than 1% of the per-capita of resources that would be required to achieve suppression in the highest-prevalence region. Such suppression would allow low-prevalence regions to reopen soon and safely, rather than maintaining lockdown or risking large loss of life. Many of these low-prevalence regions, particularly rural regions, are also highly vulnerable to the disease when it arrives. There is thus a strong case for rapidly allocating much of scarce testing and tracing capacity to these regions,

Estimates for Testing and Tracing

rather than fully focusing on testing in less vulnerable and higher-prevalence regions. This requires a focus on maximizing the mobility of testing-based suppression capacity (distinguishing from medical resources, which should be allocated to hardest-hit regions). It also crucially requires strong restrictions on travel into low-prevalence regions.

4. Within regions, already-vulnerable communities, especially essential workers, are bearing the brunt of transmission and fatalities, and should be prioritized in testing capacity. This reinforces guidelines set out in the Phase I recommendations of the Roadmap to Pandemic Resilience, with our index of vulnerability (combining measures of medical capacity, socioeconomic vulnerability, existing health disparities, and comorbidities), described in the appendix.

5. High-vulnerability but low-prevalence areas, with seemingly the lowest willingness to maintain collective quarantine, may have the most to gain from this strategy (at least until these resources arrive). Ramping up testing capacity in low prevalence, high vulnerability areas may also provide local incentives for regions with the least political will to remain in collective quarantine to maintain quarantine long enough to allow disease suppression. Low-prevalence high-vulnerability areas are overwhelmingly Republican (e.g., Fort Smith, AR, and rural West Virginia), though many are within Democratic states (e.g., Eugene, OR, and rural Hawaii). Higher-prevalence areas would then receive eventually much more capacity, but with a bit of delay.

A useful analogy in understanding our results is military strategy. The resources required to win an active battle are proportional to the size of the enemy. On the other hand, a very small force suffices to hold a region one already controls. Additional resources are of little value in regions controlled by the enemy until one musters a force of sufficient size to take that region. Once one does have sufficient forces, however, one can take the territory and ideally can quickly move troops on to another territory

Estimates for Testing and Tracing

to make additional gains. In the same way, maneuverability and careful allocation of available resources is critical to achieving victory over COVID-19.

We reach these conclusions by combining a range of models and data. We begin with data on COVID-19 and excess mortality from state public health authorities and use this to recover current disease prevalence rates based on estimates of the Infection Fatality Rate (IFR). We use this data, combined with confirmed case counts (whichever is greater) to estimate current COVID-19 prevalence. We then use a model that is calibrated to the success of Asian and Australasian countries in controlling the disease to estimate TTSI resources required to achieve disease suppression by locality, broken down by MSAs and the non-MSA areas of each state. Finally, we combine this COVID-19 specific data with the static, pre-existing, CDC-endorsed COVID-19 Community Vulnerability Index (CCVI), and incorporate epidemiological and socioeconomic factors to approximate the death toll and impact of the disease if it spreads in that community. These calculations underlie our recommendations on resource allocation.

This paper should be seen as documentation for data in the Pandemic Resilience Roadmap that we have posted at <http://www.pandemictesting.org> and <https://ethics.harvard.edu/covid-19-response>, which allow policymakers and citizens to explore recommendations and disease prevalence by geography.

We begin the paper by highlighting the flaws in current estimation approaches for required test capacity. We then discuss our methodology. Next, we turn to data on prevalence inferred from mortality. We then discuss our findings on required resources for disease suppression and possible pathways towards allocation of resources during ramp up. Then we document the tools we are making available and conclude with our plans for additional tools we are currently developing.

Estimates for Testing and Tracing

Current Data Limitations

Current Data Limitations

Current targets for testing are based on flawed data and strategy. We will first discuss data limitations, followed by a section on strategies. There is mounting evidence that the reported COVID case counts and fatality rates do not accurately reflect the reality of spread and resultant morbidity. This is largely due to a lack of testing capacity, which has led to the concentration of testing on highly symptomatic patients and therefore massively undercounts the number of asymptomatic or mild cases, which may constitute as many as half of all cases, particularly among less at-risk populations ([Henegham et al., 2020](#)). Testing capacity has been so severely limited in many areas that even many symptomatic cases have not been confirmed.

With such limited testing capacity, confirmed case counts may vary across time and space for many reasons unrelated to actual underlying disease prevalence, including the relative availability of tests and the strategy of test use (medical vs. random surveillance vs. as part of a tracing regime, etc.; see more on this in the next section). This means that targets using confirmed case counts may be not just inaccurate, but perverse. For example, if low confirmed case counts are used to lower targets for testing, this may further reduce case counts exactly as the low level of testing is increasing the disease prevalence. In this sense, a policy based on confirmed cases can lead to strategies that “chase their own tail.”

The shortage of tests has also affected fatality counts, as many hospitals have been operating under state guidance stating that, without a conclusive positive test, a fatality should not be attributed to COVID. In addition, at-home deaths are also often not attributed to COVID but form a significant percentage of COVID fatalities in high-prevalence regions, particularly in the older age cohort. The CDC itself has stated that the current data is an underestimate, likely by a significant margin. To account for this, the CSTE recently released [guidelines](#) to standardize attribution of deaths to COVID across states

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and allow for attribution without a positive test result, partly to account for this underestimation. However, these measures are insufficient for giving us a true picture of the crisis.

Some have concluded that, due to the much-higher true caseload of COVID, the case fatality rate for the disease is far lower than originally thought, perhaps as low as 0.5%. However, it is important to note that this is likely not the case. Data from countries like South Korea, with widespread testing and excellent medical facilities, still indicates a 2% fatality rate from the virus, which corresponds to the current WHO estimate and the fact that New York City has already lost nearly a quarter percent of its population.

Random samples or, better yet large-scale testing, is the best way to determine the true extent of the infection. A number of recent studies have attempted such sampling and have indicated case rates an order of magnitude greater than confirmed case counts. For example, one of the best studies, in New York City, found that [21% of the population had antibodies to the disease](#) while less than a tenth of that number have been confirmed by testing (Higgins-Dunn et al. 2020). While there have been credible critiques of these studies, they are still useful in directionally corroborating the current, order-of-magnitude level of undercounting.

Obviously in an environment of extreme test scarcity, such studies are difficult to undertake. In their absence, multiple sources of currently available data can be used to triangulate these parameters. The most promising of these methods is looking at excess death rates, that is, higher than normal death rates in a given area for a particular period of time that are not directly attributed to COVID but are likely to be COVID-related. These approaches put particular weight on excess deaths due to influenza and pneumonia-like illnesses, and excess deaths in older populations, both of which have been [spiking in recent weeks](#). Using this data, excess death-based epidemiological models have consistently concluded

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Current Data Limitations

that the true number of COVID-related deaths is likely to be two to three times the reported number. Backing this out into location-specific prevalence data, models have shown that infection counts may be as much as ten times greater than positive test counts, meaning that we are underestimating prevalence by an order of magnitude.

Looking abroad bears out these estimates, and can also help inform our outlook in the U.S. As Italy was one of the hardest hit countries—especially in regions in Northeast Italy—it is easy to see that excess deaths and preliminary serological data reinforce the fact that the official numbers are most likely undercounting both the prevalence of spread and the numbers of deaths. Some measures in Italy estimate the true numbers of death were about two-thirds larger than the official reported statistics ([Ciminelli and Garcia-Mandicó, 2020](#)) relative to 2016, while the preliminary serological data in some towns in Northeast Italy found that more than 40% of positive cases showed no symptoms ([Lavezzo et al., 2020](#)). Additionally, Italy is setting up a serological test of 150,000 individuals ([Giugliano, 2020](#)) to attempt to gain insight on the overall prevalence, rather than just rates of asymptomatic infection. This is after early studies in Germany have found, after conducting serological tests, that in severely affected regions between 10 and 15% of their population had been infected ([Regalado, 2020](#)). Moving forward, until aggressive large-scale testing is implemented, policymakers will have to rely on the signals from excess deaths and other measures of prevalence—as flawed as they are—to guard-rail their reopening frameworks.

Testing and Suppression Strategy

Another fundamental problem with many existing testing targets is their strategic goal. Testing can be used for many different purposes, as illustrated in the table below. There are four categories of testing strategies.

Estimates for Testing and Tracing

Testing and Suppression Strategy

1. **Medical tests** may be used to diagnose severe cases for the purpose of treatment, as primarily indicated by the CDC for most of the last two months.
2. **Population surveillance tests** may be used to estimate prevalence in a community, as discussed above, as indicated by the CDC since April 27.
3. **Universal testing** may be applied broadly (possibly within particular communities, such as essential workers) on a regular or random basis to remove the disease directly from a target population as advocated by [Romer \(2020\)](#).
4. **TTSI testing** may be used to suppress the disease, as prescribed in the [Roadmap to Pandemic Resilience](#).

	Suppression	Mitigation
Case-Based	TTSI	Medical
Population-Based	Universal	Population Surveillance

The testing capacity required for each of these strategies to meet its objective is radically different. For example, the testing requirements of the first and fourth strategies vary roughly linearly with disease prevalence, as both aim to target actual cases and follow up on them. The second and third strategies are largely independent of disease prevalence, but rather aim at populations. The first strategy requires far less testing than the fourth, and the second far less than the third, as these focus on small subsets

Estimates for Testing and Tracing

Testing and Suppression Strategy

of the relevant group (acute cases or samples) rather than testing the entirety of the relevant group or multiples of it, as is the case with tracing. Targets thus far have been mostly based on medical uses and to a limited extent on population surveillance, detection, and universal testing. Targets for a TTSI strategy are significantly more subtle and multidimensional, as we will see below.

While we see a real role for each of these forms of testing, we believe the bulk of tests and thus the primary focus of targets should be on TTSI. While medical uses are critical (except possibly in regions where prevalence is high enough that symptomatic diagnosis and/or the use of CT scans may be fairly accurate), it will constitute a small fraction of the tests required for TTSI and thus will make a negligible contribution to TTSI-oriented targets. Similarly, population surveillance, while critical, will require far fewer tests than TTSI and thus does not significantly add to testing targets if we adopt either TTSI or universal testing.

Thus we are left with a choice of whether to attempt to suppress the disease (strategies 3 or 4) and, if so, which of these to use. For reasons discussed in the [Roadmap to Pandemic Resilience](#), we believe that disease suppression should be our goal as, absent this, we are stuck between the Scylla of a year or more of a frozen economy and the Charybdis of millions of deaths, likely both. With disease suppression as our goal, the choice is then between universal testing (perhaps within certain vulnerable communities) and TTSI.

As several recent papers show (e.g., [Reich et al., 2020](#)), the testing requirements for disease suppression under universal testing are at least an order of magnitude greater than under TTSI, even when disease prevalence is quite high, since universal testing must be quite frequent to suppress the disease. As we will soon see, even this analysis dramatically understated the gains from TTSI over a universal testing policy, as it did not take advantage of the extent to which TTSI can take advantage of low

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prevalence. A more accurate estimate appears to be that universal testing requires hundreds of times more total tests ([Cleevely et al., 2020](#)) than TTSI does, and even then is likely to be significantly less effective ([Kucharski et al., 2020](#)).

Given that present testing capacity is still an order of magnitude below that required for TTSI, universal testing, whatever its benefits, will require many more months of lockdown to prepare, will have a much higher aggregate cost and thus may be too costly for many jurisdictions to implement, would rely on certificates of recent negative tests to access public amenities, and may have more serious civil liberty and equality challenges. For all these reasons, TTSI seems by far the more desirable path, and thus we believe that appropriate targets should be derived from this framework.

However, the sophistication of the TTSI strategy makes it substantially more difficult to model and estimate resource requirements as compared to the other strategies; consequently, we devote the rest of this section to highlighting how the strategy works and some of the subtleties of the strategy that previous analyses have missed.

The essence of TTSI is to follow up on confirmed cases of the disease by searching for people the confirmed individuals has had contact with (and therefore may have spread the disease to), testing those contacts, and isolating those who test positive. The chain is continued until no positive cases are detected; this is usually two to three rounds, but more if infections are caught later.¹² If additional

¹² Precisely what happens to those who test negative in this process differs across versions of TTSI; they may be quarantined, released, or temporarily quarantined and then released after a second negative test. The first option conserves tests most strongly, but the second two options allow more people to return to society. We focus on the first option in what follows; with other options we would need roughly twice as many tests.

To see why we should expect two to three rounds of tracing to suffice, note that symptomatic individuals have typically infected a single other individual prior to becoming symptomatic, according to recent estimates of pre-symptomatic shed ([Cheng et al., 2020](#)). Assuming that viral shed is uniform across the pre-symptomatic period, the second individual will only have been infected for half as long (given that, on average, they will have received the infection halfway through the infection period), so we should expect them to have infected half another individual. This individual will in turn have infected one-quarter of an individual (as they will have been infected for half as long), and will have done so only if they were themselves infected (which is expected to occur only half of the time) and so forth. The expected number of rounds will thus be $1 + 1 + \frac{1}{2} + \frac{1}{2} \times \frac{1}{4} + \frac{1}{2} \times \frac{1}{4} \times \frac{1}{8} + \dots = 2.64$. This idealized series will be somewhat worse in practice due to tracing delays, so we assume an average of 5 in our numerical results.

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tests are available once all such contacts have been followed, they are allocated to achieving broader tests of symptomatic individuals (viz. those insufficiently symptomatic to come into clinical settings) and, after this, to increasingly frequent routine testing in sectors with potential for more intense exposure or dangerous spread, such as health care or long-term care facilities. As above, all positive cases are traced and the chain followed until all following cases are identified.

Because TTSI focuses on following up on contacts of positive cases and most tests are used to perform this follow up (because a typical individual will have at least ten contacts), the number of tests required for the strategy to succeed is roughly proportional to the prevalence of the disease, though the multiplier may be higher in denser areas where individuals have more contacts. Our analysis below ignores the issue of density, as it would only further exaggerate our conclusions that fewer resources are required in less dense areas, but we hope future research will account for this.

At the same time, because TTSI rapidly traces down subsequent cases, it has the potential to quickly identify most cases and thus allow rapid suppression of the disease. This potential has been realized empirically in many countries, such as South Korea and New Zealand, that have applied this methodology and rapidly suppressed the disease.

This rapid disease suppression, in turn, means that prevalence and thus the number of tests required for TTSI will fall rapidly as the strategy is applied. Thus the capacity, both in terms of tracers and tests, required for TTSI is not static. A powerful surge is needed in a community, followed by a quick decay. Thinking about capacity in terms of tests per day may be inappropriate because surge capacity per day will greatly exceed later capacity and in fact the total number of tests required may only be a small multiple of a single-day surge capacity. Once the disease is suppressed, the required tests per day may fall to very low maintenance levels, perhaps similar to those required for population surveillance.

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Testing and Suppression Strategy

Furthermore, the speed at which test results can be returned (the latency of tests) is at least as critical a variable. TTSI relies on rapid follow up to minimize spread. The faster test results are returned, the more rapid follow-up can be. Assigning multiple contact tracers to a single case has a similar value.

Finally and perhaps most importantly for what follows, to the extent that capacity can be mobile across jurisdictions and travel can be contained (by remoteness, moral suasion, or enforcement), it may be possible to use these features to dramatically reduce the number of tests required to achieve disease suppression. Mobile capacity could enter a jurisdiction, suppress the disease and then relatively quickly mostly move on, leaving behind only maintenance capacity. To the extent that mobile testing capacity may need to be significantly sequenced across areas, given limitations, it is possible that the total simultaneous capacity might be far below estimates of testing capacity for disease suppression that is carried out simultaneously and nationwide. Particularly attractive is quick suppression in current low-prevalence areas at existing levels of testing that would then allow mobile testing to move on to progressively higher-prevalence areas, ensuring that low-prevalence areas do not quickly balloon into high-prevalence areas, with the accompanying loss of life.

The TTSI strategy is demanding along many dimensions. It requires a high degree of coordination, disruption, and sequencing (and thus delays in reopening some areas). It is also somewhat counterintuitive in that it allocates resources first to low-prevalence areas rather than hot spots, and it doesn't build permanent capacity. All of these reasons may limit the extent of its practical value, and it is not by any means a perfect, or sufficiently complexified, prescription for overall suppression. However, the TTSI strategy does take into account and work with current capacity, as well as nuance the overwhelming focus thus far on the "tests per day" number, suggesting the use of a broader range of metrics such as vulnerability, latency, and total number of tests required.

Estimates for Testing and Tracing

Testing and Suppression Strategy

Strategies of this sort are actually fairly familiar in another context, namely military conflict. In such contexts, it is widely understood that speed, maneuverability, and the overall size of a force are at least as important as the number of troops available per unit population. This is why, for example, the U.S. military regularly pays ten times as much for a plane that is 30% faster, or why tanks proved so devastatingly effective in the Second World War.

In such contexts it is useful to think of there being three kinds of areas, which we will refer to extensively below; these are areas we hold (green areas), areas held by the enemy (red), and contested areas (yellow). In the green areas, the disease is mostly absent (our threshold is a current infection prevalence of less than one per 36,000). When we began this work there were units we measured that fell into this category, but at present we cannot detect any, though there are many that are close. In the red areas, the disease is so prevalent that the distinction between TTSI and universal testing fades, as following tracing chains covers a large part of the population (our threshold for this is 1% of the population). Given limited but growing resources for testing and tracing, preventing major outbreaks appears best done via an outside-in strategy, where we organize to ensure surge capacity for testing in communities that are close to green, fully support TTSI in yellow communities, and build capacity towards testing and tracing, while also providing medical resources and extending lockdown, in red communities.

While these principles give us a sense of the associated strategy, it is important to also understand the tactics underlying TTSI, which involve the rapid follow-up of tests with tracing and further tests. Suppose we test person A and start the clock. We send this test to the lab and get the test results back, showing that person A has tested positive. We mobilize a trace team, who talk to A and develop a list of exposed people; they contact people on this list and test them. We stop the clock when those at-risk individuals (person A's contacts) have been given a test. All of this is the "trace time." This process needs to move fast—any delays to check and confirm will likely lead to more deaths than it saves. A trace time

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beyond three days has little value in controlling the epidemic while a trace time of one day is plausibly typically effective. [See a recent article in Science](#), particularly figure 3, which shows the effectiveness of contact tracing.

Achieving a one-day trace time appears possible, although it requires an optimized process. For example, testing facilities that support contact tracing must be dispersed across the country to avoid significant transport delays, the tracing process should be ready to go 24 hours a day, and significant organization is required.

Note that there is a role for slower testing systems as well—they can be used to discover unknown outbreaks through wide-scale surveillance of symptomatic individuals. Thus, we envision two types of forces here: agile forces used for “hot pursuit” contact tracing and slower-moving forces used to discover outbreaks by testing symptomatic individuals. We plausibly have sufficient slower-moving capacity for surveillance across the nation, so our focus as a nation should be on buildout of agile capacity. Note that agile tests can be used for slow-moving purposes, but the opposite is not true, since by the time slow-moving test results come back the disease has already been transmitted to new people.

Finally, we note that there may be strategies that economize on testing more effectively than the one we outline here. For example, in red regions, it is reasonable to infer that symptomatic patients have COVID-19 given the high prevalence and/or it may suffice to make a diagnosis by CT scan. One may then trace contacts, and quarantine contacts without testing. If some tests are available, these may be allocated to test essential workers among this traced population or contacts who may have disproportionately spread the virus, or to pooled testing of the other contacts identified. Similarly, in yellow areas, pooled testing may reduce testing needs, perhaps by a significant factor. We do not factor these into

Estimates for Testing and Tracing

Testing and Suppression Strategy

our analysis as our goal here is to derive targets for areas to aim for rather than exclusively to focus on the best intra-region allocation of extremely scarce tests. Given that there are few real-world examples of using these techniques to effectively control the disease, we are concerned they may fail. However, red and yellow regions with severely limited testing capacity may be forced to pioneer their application.

02 Modeling Methods

Step 1: Modeling current prevalence and susceptibility

Using current data on deaths (discarding data on cases and tests, due to major disparities), we first estimate the rate of infection by assuming infection fatality rates follow a distribution given by the CCVI (see step 3 below). Where this is below current confirmed case counts, we use these.

Step 2: Modeling required testing capacity

Based on estimates from successful regions such as South Korea, we estimate the necessary number of tests to detect positive cases *and* suppress all transmissions generated by them. We also analyze the capacity required to maintain green regions by assuming this equals the per-capita capacity used for such maintenance successfully in South Korea. We combine this with the previous projections to arrive at necessary testing capacity.

Step 3: Modeling community risk and prioritization

Given resource constraints, it is crucial to allocate testing to regions where it can be most useful. We apply metrics of vulnerability across counties to determine where testing can be deployed to greatest effect, not only to save the most lives but also to prevent future surges in testing necessity with new outbreaks. Our measure of vulnerability is the COVID-19 Community Vulnerability Index (CCVI; <https://precisionforcovid.org/ccvi>). The CCVI combines six themes: four from the CDC's Social Vulnerability Index, plus epidemiological risk factors and healthcare infrastructure factors (see [detailed methodology](#)). The CCVI is calculated at the census tract, county, MSA, and state level as a rank, expressed from low (0) to high (1) vulnerability. We bucket this into three categories: low (bottom 20% of CCVI), medium (middle 60%) and high risk (top 20%), and assume an IFR of .08, .1 and .125, respectively, for these categories, as this represents the variation estimated across provinces in Italy for IFRs.

Modeling Methods

Prevalence and Regional Classification

Prevalence and Regional Classification

We begin by discussing the distribution and classification of disease prevalence across the country. As discussed above, we divide the country into its MSAs and “rural states” (states minus all MSAs). According to our estimates, prevalence varies dramatically across areas thus defined. In some areas (such Chico, CA, and Fort Smith, AR) less than one in 10,000 individuals have the disease at present, while in others (especially New Jersey and New York) we estimate that more than one in every 60 people has the disease at present, as high as the projected peak of an uncontrolled disease spread. Most of the population is at an intermediate level. Overall, one in 300 Americans have the disease and the median American lives in a region where one in every 500 people has the disease.

As discussed above, it is analytically useful to break regions into three categories. Green regions are ones where we calculate that long-term maintenance capacity suffices to suppress the disease at present, which occurs when no more than one in every 36,000 people has the disease. As of this draft, no areas are green, though this appears to be a recent development as we were writing this paper. Roughly 30% of the country is living in areas with prevalence below one in 1000.

On the other extreme are red regions, where more than one in every 100 people have the disease. Because TTSI will not just test those who have the disease, but will also usually test many of their contacts (and contacts of their contacts), in these regions the distinction between TTSI and universal testing starts to blur, since over the course of applying TTSI, most of the population would need to be tested as a contact of someone with the disease. The fraction of the population living in such regions is a bit less than 10%. These regions are mostly in the Northeast, though there are exceptions (such as Sioux City, IA, and Albany, GA).

Modeling Methods

Prevalence and Regional Classification

Finally, most of the country (about 300 million) falls into the intermediate yellow category, which is between these two extremes. Clearly these areas have a wide range of disease prevalence and they cover most of the country (e.g., Springfield, MA is nearly red, and Chico, CA, is nearly green). Figure 1 shows a plot of the country on the spectrum from nearly green to red.

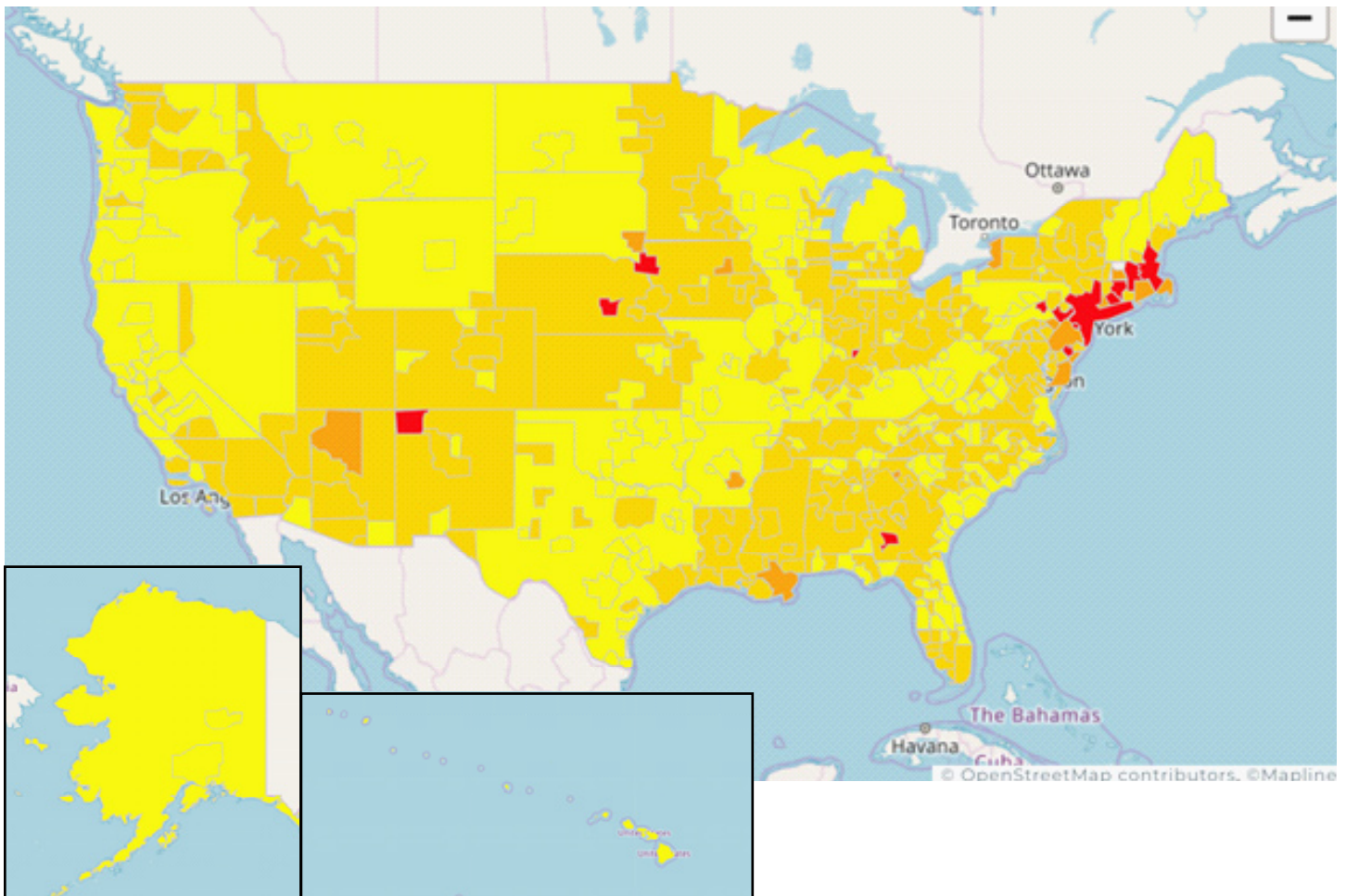


Figure 1: Region by Color

Key:

Red: Prevalence of 1 in 100 or higher

Orange-Yellow: Yellow areas close to red, prevalence between 0.6 in 100 and 1 in 100

Fully Yellow: Prevalence lower than 0.6 in 100

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03 Aggregate Resource Requirements

We now turn to our central analysis of targets for testing capacity. We begin by discussing and interpreting aggregate testing and tracing capability.

As noted above, there are several importantly different ways to describe the required testing capacity. First, we can consider the maximum surge capacity we would need if we were to simultaneously begin applying TTSI in all parts of the country based on current prevalence. This is about 5 million tests/day, equal to the focal numbers from Siddarth and Weyl, and the Roadmap to Pandemic Resilience.

However, depending on the precise sequencing we apply, the implications for total testing resources required and even the requisite capacity at any moment may be quite different. In particular, we also estimate that the total number of tests required to complete TTSI across the country is under 200 million. This is less by only about six weeks of testing at the peak rate, in contrast to the cost calculations in other work suggesting that peak levels of capacity could persist for as long as one to two years, which would imply more than a billion total tests. In contrast, after a short initial surge, our calculations suggest that maintenance would require testing only a fraction of a percent of the population each day, adding at most hundreds of millions more tests over the course of the epidemic. A similar calculation applies to contact tracers: while our calculations suggest we may need significantly more contact tracers at a surge point if they are conducted simultaneously throughout the country compared to what other estimates have suggested (as many as a million), this will wind down to a maintenance level of only tens of thousands.

At minimum this suggests that the total resources needed for TTSI is likely to be significantly lower than previous calculations suggested. Yet there is an even more feasible possibility to the extent that suppression can take place asynchronously. One may never need to reach the full surge capacity in order

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to suppress the disease. Clearing out the disease would take a month if we reached 5 million tests/day. But if we had to wait two months due to limited capacity, the same could be accomplished with half the daily testing capacity.

Obviously, there would be many downsides to such delay and sequencing:

1. Most importantly, delay and sequencing would drag out the period when much of the population remains in collective quarantine, and lives could be lost during this time.
2. Sequencing might be difficult to coordinate and would fuel tensions across regions as some would emerge from lockdown sooner than others.
3. To succeed, one would have to begin with regions where travel is either naturally or artificially restricted inward from red regions. Given how rural many red and yellow regions are, however, this might be feasible without too much legal intervention.

Despite these challenges, the possibility of sequencing and avoiding the absolute requirement for simultaneity opens important possibilities at least along the edges of the strategy. For example, under the phasing discussed in Roadmap to Pandemic Resilience, little progress occurs until the entire essential workforce is stabilized and protected nationwide. This means waiting for a massive ramp-up of capacity to take place before anywhere can open. Our analysis here suggests that whole localities and subregions, especially those with low prevalence, might stabilize and protect their essential workforces and begin to reopen ahead of the country as a whole. This would create substantially greater flexibility and adaptability in the face of setbacks to testing supply than is possible in the strategy described in the Roadmap to Pandemic Resilience.

Aggregate Resource Requirements

Resource Requirements by Localities

Resource Requirements by Localities

Now we turn to our disaggregated estimates of resource requirements for disease suppression in different localities. We display these in Figure 2, in terms of per population maximum per-day surge capacity of tests required for disease suppression. The remarkable thing about this is how wildly heterogeneous this is across regions. This follows directly from the vastly different disease prevalence across regions.

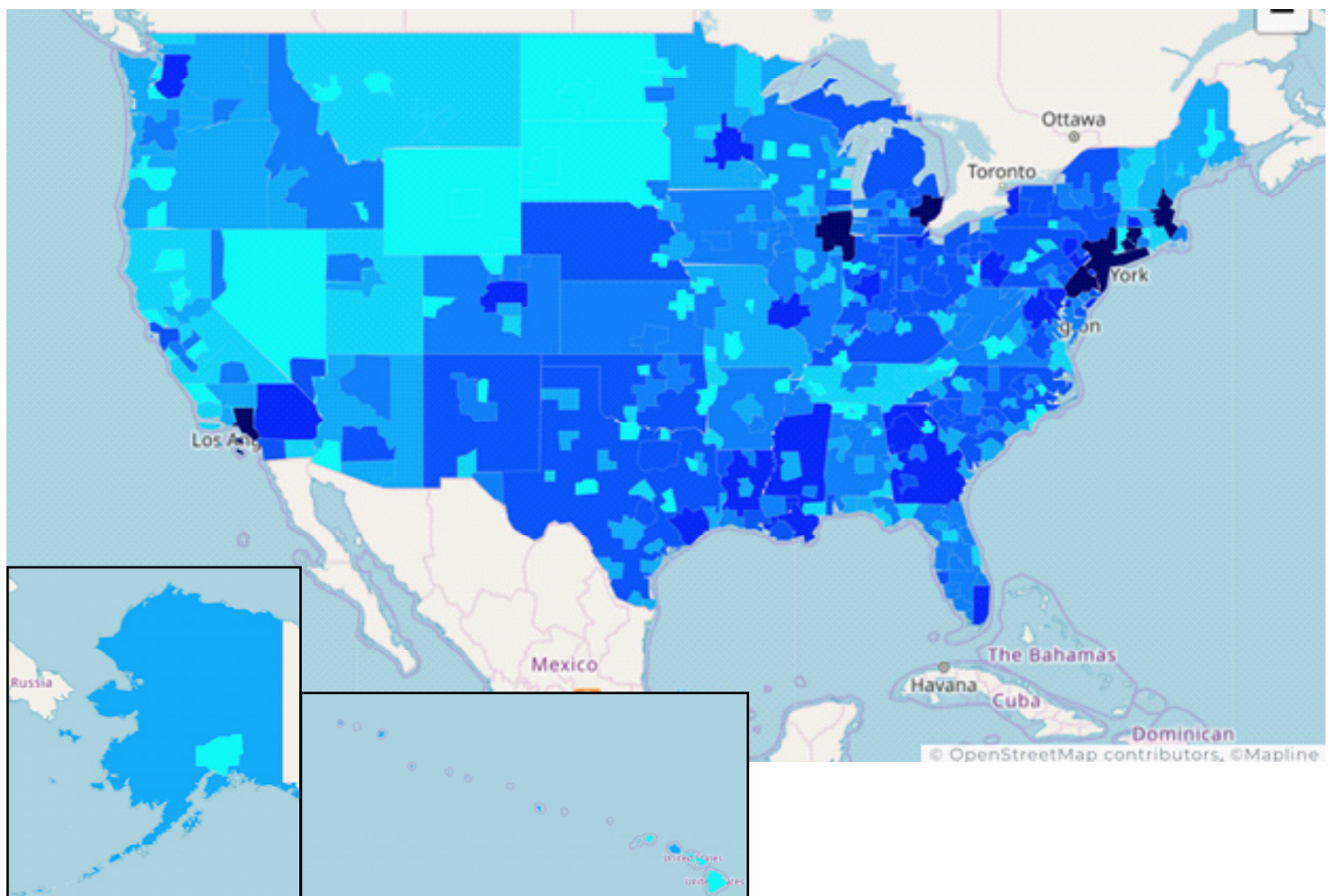
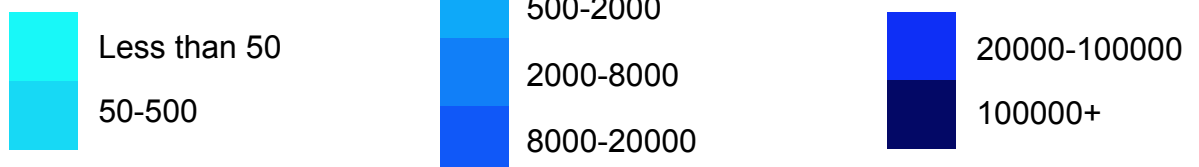


Figure 2: Surge Capacity Tests per Day:

Key:



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Aggregate Resource Requirements

Resource Requirements by Localities

For example, if you take the lowest prevalence areas that account for 10% of the population, they require less than 60,000 tests per day to test the required roughly .2% of their population a day needed to suppress the disease. This is less than a fifth of current testing capacity, and about a hundredth of what would be required to suppress the disease nationally. And yet, for this number, we can protect nearly a tenth of the U.S. population, at least if travel into these regions is limited so this protection is not undermined by interregional spread.

Yellow regions overall clearly have much higher needs. They require about 3 million tests per day in an initial surge to fully suppress the disease. Yet even this is less than two-thirds of the requirements for full national disease suppression, but it covers more than 90% of the population. In contrast, red regions, with less than 10% of the national population, themselves require 2 million tests per day to suppress the disease. Much the same story applies to tracing capacity.

Targeting Resource Allocation

Focusing on lives to be saved further reinforces this picture Red areas less vulnerable than other areas are. On average they are in the 37th percentile of the CCVI score, while the average yellow region is over the median of the CCVI. Pulling out per capita income and poverty confirms this picture, with yellow regions exhibiting a significantly lower income level than red regions.

However, it should be noted that red regions are somewhat more diverse on average, with a 5% higher non-white population. Both differences are likely explained by the fact that high-prevalence cities, with higher income per capita and greater diversity, are contained largely within red regions. This points to the fact that racial health disparities will likely need to be additionally addressed at the local level, since these disparities often manifest within, rather than between large, MSA-level regions. However, this does not take away from the need for low-prevalence regions to invest in testing and tracing up front. In fact, if high-vulnerability, low-prevalence areas do not act quickly, large-scale outbreaks are likely to occur and persist, and these will likely exacerbate existing racial and socioeconomic divides within those regions, as has been seen in other geographies such as New York City.

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Aggregate Resource Requirements

Targeting Resource Allocation

Thus, the potential to save lives with limited testing resources is vastly greater in low-prevalence, high-vulnerability yellow regions than in high-prevalence, low-vulnerability red ones. Figure 3 illustrates this by coloring the map according to lives saved per unit of tests/day in surge capacity invested. The range of this variable is remarkable. In an average yellow region, an initial surge capacity of one test per day would suppress the disease sufficiently to clear out an area with one person living there, while in a red area, an initial surge capacity of five tests per day would be needed to clear an area where one person lives. Yet if we disaggregate further things are yet more extreme.

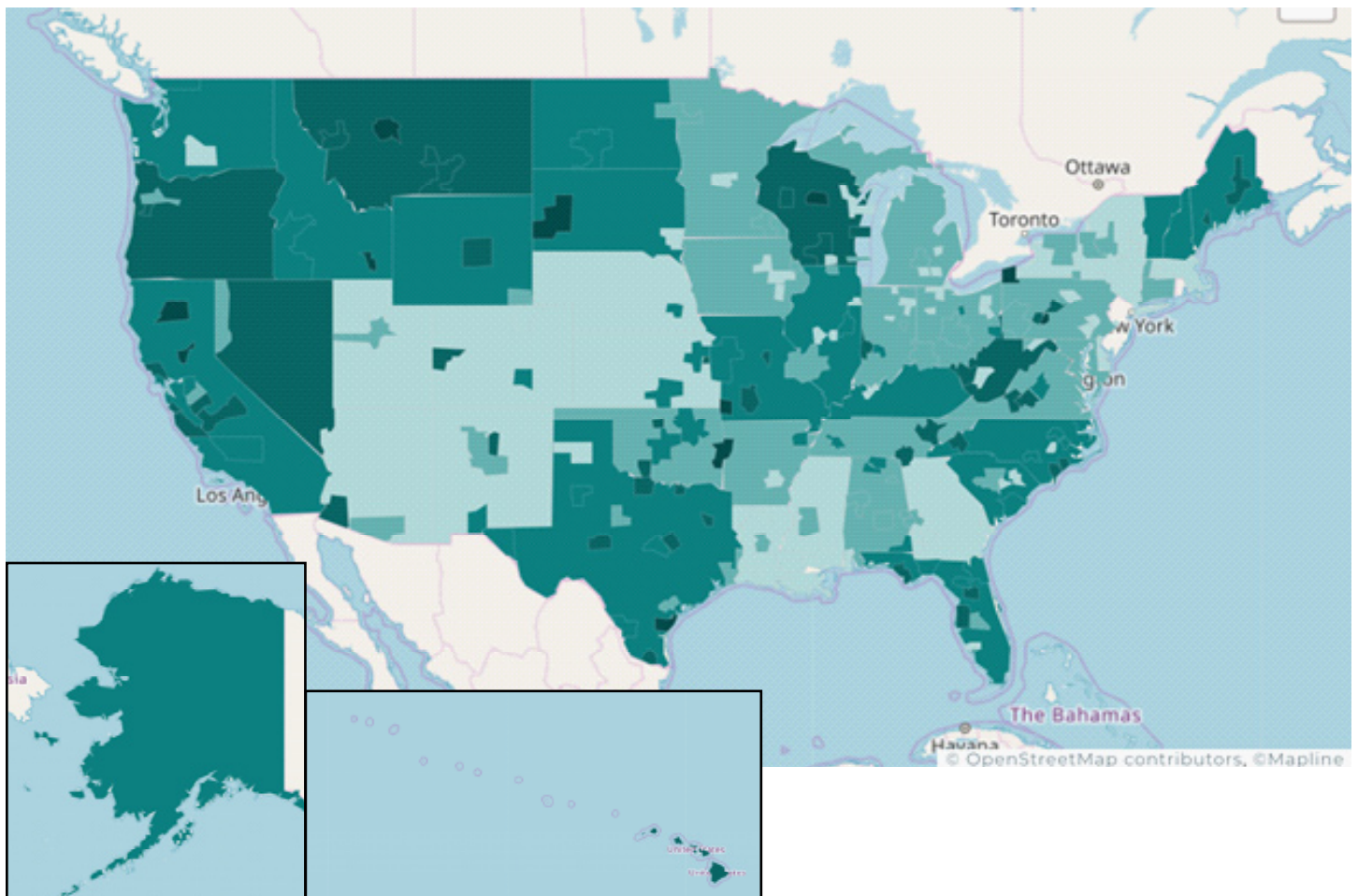


Figure 3: Lives Saved per Unit of Tests per Day:

Key:



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Aggregate Resource Requirements

Targeting Resource Allocation

Fort Smith, Arkansas, is the greenest region and one of the most vulnerable areas of the country according to the CCVI, at the 85th percentile of vulnerability. It has a heavily African-American and Hispanic population (nearly 30%) and a per capita income well below half the national average. We estimate that a capacity of just over 100 tests per day would stabilize this MSA of 250,000 people with more than 3000 lives at jeopardy.

Contrast this to the lowest lives-per-test-capacity MSA, Poughkeepsie in New York, adjoining the home of one of the authors of this paper. There we would need almost 10 tests/day to stabilize the population for each life at jeopardy. Furthermore, Poughkeepsie-Newburgh is extremely white (nearly 70%) and wealthy (per-capita income above the national median). The ratio of Poughkeepsie to Fort Smith is thus almost 400:1. Given present limits in capacity, it is thus vastly more effective send tests to Fort Smith, rather than to Poughkeepsie.

Yet while it might seem that such decisions would require a national resource allocation system implausible in a federal system, it is important to note that stark differences exist even at the state level. Let us consider Arkansas and New York. In Arkansas, the red Pine Bluff MSA is at roughly .2 lives per test/day capacity, as compared to the 30 in Fort Smith, a factor of more than a hundred difference (though it should be noted that Pine Bluff is one of the poorest and most heavily African-American MSAs in the country, so there are distributive justice reasons to attend carefully to its needs). Even within New York, one of the hardest hit states, the Watertown-Fort Drum MSA requires less than a fortieth as many tests per day per life saved than does Poughkeepsie.

Many states are as or more extreme as this. While we acknowledge that delivering tests to more rural areas may have greater financial cost, this factor is likely relatively minor compared to the large differences we find. For example, Joplin, Missouri, is a nearly green and quite vulnerable MSA, with almost

Aggregate Resource Requirements

Targeting Resource Allocation

twenty lives saved per test/day capacity. It is in the top 25% of most vulnerable population and has almost half national per capita income, with only 15% of the population above the poverty line. In contrast, St. Louis is nearly red, at around a half of a life per test/day capacity, again a thirtieth of Joplin, and it is below median in vulnerability.

Figure 4 performs an illustrative exercise, showing what fraction of the potential total lives to save that are covered by different fractions of total testing needs. With just 1% of national surge test/day capacity, we can suppress the disease in areas representing almost 10% of the lives to be lost. With 10% of the capacity, hardly above what we currently have, we suppress the disease in areas representing more than 40% of potential lives. On the other hand, to get the last 10% requires more than a third of surge testing capacity per day.

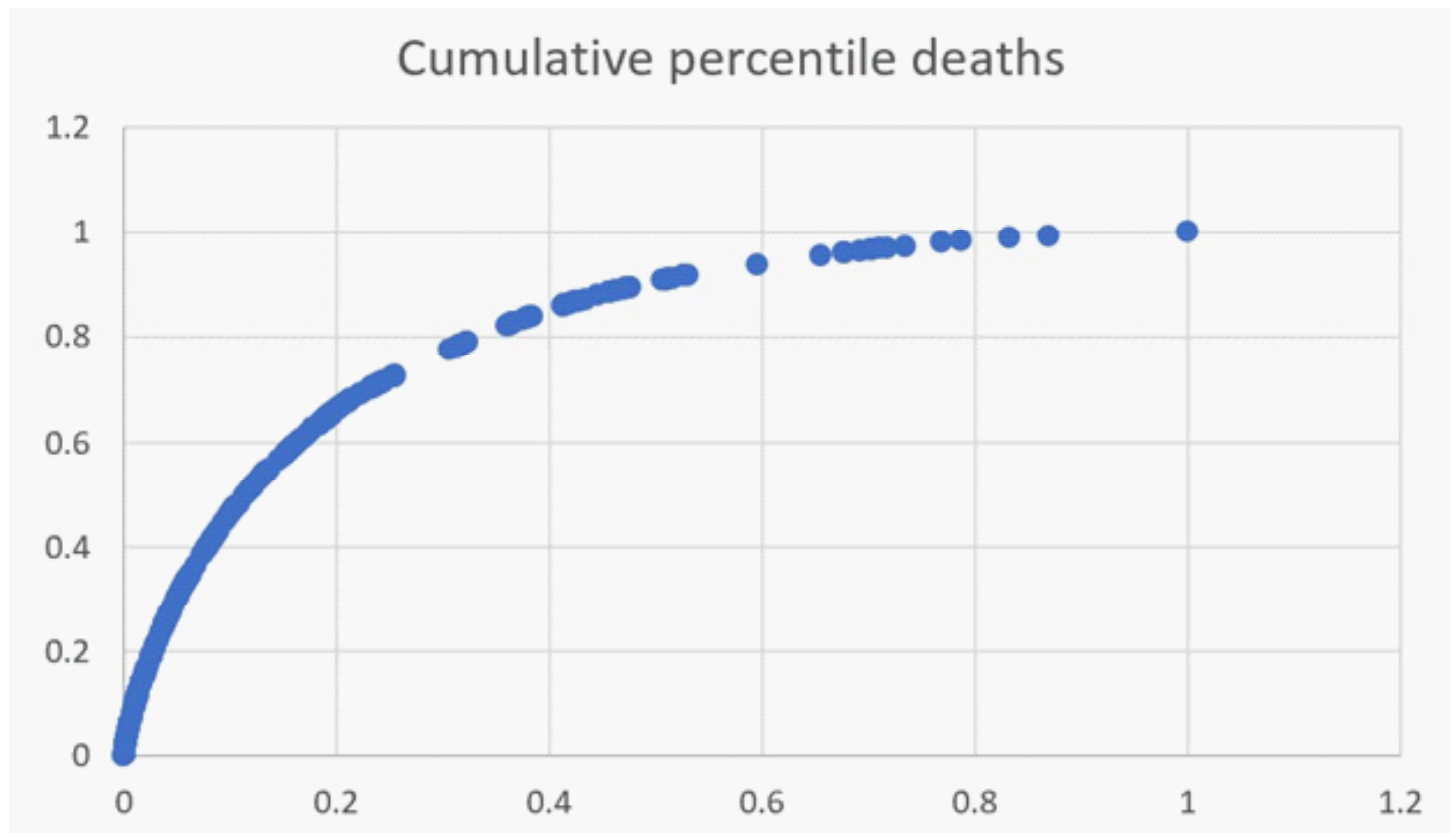


Figure 4: Cumulative Tests

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04 The Equity and Politics of Prioritization

The above logic may initially seem cold and counterintuitive. Who could be in favor of denying testing resources to regions that are in desperate straits, instead to furnish them in regions of relatively low prevalence? It seems like the ultimate example of economic efficiency logic trumping sound politics, or more importantly, justice.

Obviously we should not take these results overly literally, as there are a wide range of issues standing in the way of such a strict prioritization being either feasible or desirable.

- The number of estimated cases relies in part on the CCVI and a particular relationship between it and infection fatality rates, which has little empirical basis.
- Our model also relies heavily on the CCVI to ensure that focusing away testing capacity from high-prevalence areas does not exacerbate existing COVID-19 transmission and fatality disparities by race, ethnicity, and socioeconomic status.
- Our model ignores intra-regional variation; there are likely to be needy, low-prevalence facilities in high-prevalence regions, particularly in sites of essential work, that we would neglect under a strict adherence to this approach. Decentralized, local deployments of this strategy should be targeted towards mitigating this.
- Our model also neglects medical, population surveillance, and universal testing uses of test capacity, some of which may need to vary more directly, heavily, and inescapably with prevalence.
- Our model does not offer any additional clarity on the role of essential workers, on which the Roadmap to Pandemic Resilience appropriately focused as the first population to stabilize and protect, beyond recommending an adherence to these guidelines.
- Our model may insufficiently allocate testing to tribal lands like the Navajo Nation, which is spread across MSAs and faces significant barriers to testing and treatment.
- Our model relies heavily on limited travel into low-prevalence regions, which is only likely feasible in a limited set of cases.

The Equity and Politics of Prioritization

Yet, the strategy may not be quite as naïve about justice and intuition as it might at first appear. While it seems to focus exclusively on efficiency, in fact it is heavily focused on equity. It puts enormous weight—and very intentionally so—on allocating resources to the regions that are most medically and socioeconomically vulnerable to the disease, as this directly enters the calculus in determining infection fatality rate as well as the associated prevalence level. It also does not recommend that other needed resources be funneled first towards low-prevalence areas, only tests and associated tracing, which have a very specific function in the timeline of disease response. High-prevalence areas should still be the priority for medical and hospitalization resources.

Furthermore, the political logic behind the strategy is more realistic than it may at first seem. It tends to recommend first testing in under-resourced, less dense, and more Republican regions, regions that because of both their politics and their low prevalence are increasingly focused on coming out of collective quarantine very quickly. Any politically realistic plan has to account for this focus, as well as for the progression of the disease elsewhere and the current limits in testing capacity; we are aware that this strategy, more than other strategies, clearly does consider these issues.

On the one hand, this model allows areas that have been only lightly touched by the virus but are both socioeconomically and epidemiologically vulnerable to end lockdown and be free of the threat of the virus sooner. It also gives them strong grounds for limiting travel from high-prevalence regions, and there is already substantial sentiment in favor of that limitation. On the other hand, our model gives these regions a very strong incentive not to break collective quarantine and allow prevalence to rise, as their frontline access to testing capacity will depend on keeping prevalence down. This may be just enough to provide these regions with a reason to maintain collective quarantine just long enough to ensure that they can suppress the disease and maintain their status as a low-prevalence area. This policy may thus not merely be the most efficient, but it may also share important features with plans built around

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The Equity and Politics of Prioritization

political realities and equity concerns. Given the reality of our testing capacity and the extent to which the disease has been allowed to progress in some regions, this is the best option left to protect the most lives.

Nonetheless our results should be interpreted with significant caution and they do not provide any direct policy prescriptions. Many more details of within or cross-regional disparities will be critical to making such prescriptions. Rather than providing direct policy, we hope to illustrate a directional methodology to think about such disparities quantitatively and incorporate them into resource allocation in the context of a conflict against a pandemic.

05 Conclusions

Despite these caveats, there are crucial, high-impact takeaways from this white paper that should be used to inform effective suppression policy. First among these is the immediate need for states and locations with currently low COVID-19 prevalence to invest in and call for large-scale surge capacity for PCR testing and contact tracing. These locations have the opportunity to avoid the tragic loss of life that accompanies the inevitable ballooning from low- to high-prevalence that will result from reopening without a TTSI procedure in place. To take advantage of this opportunity, they will have to act quickly and will require federal support for this unprecedented ramp-up of capacity. Given current limitations on testing capacity, this will require a counter-intuitive push for testing in low-prevalence areas as capacity is built up, rather than focusing exclusively on testing in current hotspots.

Secondly, our model estimates up to millions of daily tests needed for a suppression strategy in high-prevalence areas, for example around New York, which is two to three orders of magnitude higher per population than in low-prevalence areas. Given current capacity restrictions, these areas will need to extend lockdown as this capacity is built-up. A much larger net must be cast with regards to quarantine, with as many contacts quarantined as possible and the requisite investment in supported isolation, in addition to the general lockdown. This will allow for greater protection for essential worker populations and other vulnerable communities, as well as for affected facilities such as prisons and food processing plants, as testing ramps up. These regions should also be prioritized for other, non-testing resources, such as medical supplies and therapies.

Finally, our work highlights the need for disaggregation in developing and implementing successful response strategies. We show that different areas and different communities face different levels of risk with regards to the virus. In addition, the specific impact of increased testing capacity is vastly different across regions and communities, given the timeline of the disease. We illustrate what can be possible

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Conclusions

with a combination of federal-level coordination and disaggregated, local targeting and tailored policy. We have already lost more lives than we should and we must act quickly to prevent further escalation. Nation-level suppression can only come from the judicious deployment of our current, limited testing capacity where it can do the most good, and concurrent ramp-up of capacity to suppress the pandemic nationwide.

Many more questions are left unanswered than those we have managed to address here. There is a desperate need for careful work on how to use extremely limited testing capacity most effectively in red areas that have generally strong city administrations, information technology etc. but will be for some time desperately low on testing capacity. Targeting limited tests as efficiently as possible will be critical to stabilizing essential worker populations and allowing some resumption of economic activity. Significant efficiency gains may also be possible in yellow areas, where low prevalence makes pooling possible. Much more work is needed on mobility patterns and how realistic it is to limit mobility across areas, as well as on the best micro-protocols for TTSI (e.g., What is the precise mixture of testing, quarantining, etc. to use?). Quantitative dependence on test latency in all regimes remains unclear. We look forward to work clarifying these questions in the coming weeks as states begin to implement plans based on these principles.

Acknowledgements

We deeply appreciate the help of Vi Hart and Cameron Jarrell in creating the visualizations for this work.

06 Appendix: Further Discussion and Definitions

Community

In the context of a virus, a community is a group of people that cannot be easily split apart into two groups that would have few chances to infect each other. This is an inexact definition, but it is crucial to understand since you cannot use contact tracing for only half of a community to effectively suppress the virus because the other half of the community will constantly keep reinfecting the half that is contact tracing. Stated another way, treating Manhattan as its own community is not useful since more than half of the people who work there come from off the island.

There are 392 Metropolitan Statistical Area (MSA) in the United States which provide a working definition of community for most of the population. There are several thousand smaller urban clusters which may also be good targets for analysis ([see the distribution on the US Census Bureau website](#)). These two types of urban regions account for 80% of the US population. For more rural locations, a geographic area large enough that most people do not leave it on a daily basis is a community. A plausible unit for those areas is a county. Though communities are defined for social, political, and economic reasons, they are also a good approximation of the regions we should be dealing with in planning how to handle a shift from lockdowns to a TTSI strategy (see [Angel et al. 2020](#) for a discussion of spread through MSAs.)

Every community is currently either green, yellow, or red. Green communities have no known active infections. Yellow communities have known a small number of active infections which public health authorities are handling. Red communities have an outbreak which public health authorities cannot suppress.

Appendix: Further Discussion and Definitions

Plans for Communities

Green communities are the easiest to deal with—we just need to allocate sufficient slow-lane testing capacity to cover all symptomatic individuals. Since we are headed into summer, seasonal illnesses are declining, so this should be easy. We should also be prepared to assist green communities if they transition to yellow so that we can efficiently get them back to green. Since many of our green communities are rural, it makes sense to have mobile testing facilities ready to move there, train local people to do contact tracing as a reserve, and set up contingent agreements with hotels or motels to support isolation. With these preparations, green communities can end lockdowns and if outbreaks occur, they can suppress them by TTSI rather than further lockdowns.

Stabilizing yellow communities requires active investment into fast-lane testing. Many of these communities are doing contact tracing right now, but they are either bordering on overwhelmed or not working with sufficient alacrity. In order to get the tracing time under one day, it is necessary to beef up the contact tracing corps in these communities with both personnel and fast systems or procedures. Finally, supported isolation locations such as hotels dedicated to the purpose need to be put into active use. Many people going to such hotels (or isolating in their house) are not infected—they are simply contacts of an infected person and are isolating to protect family, friends, and community. The precise criteria for who is a contact should be driven by data, but a conservative approach suggests that a contact is a person who has been within 2 meters of an infected individual during the previous two weeks. If all contacts isolate for two weeks, are tested immediately using a fast-lane test, and have follow-up fast-lane tests if they become symptomatic, then the number of active infections should rapidly decline in yellow communities. Once we have sufficient capacity to execute TTSI with a trace time of less than one day, we should be able to move up at least one phase in the TTSI plan and possibly more.

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Appendix: Further Discussion and Definitions

Plans for Communities

Plans for Communities

Stabilizing red communities is similar to stabilizing yellow communities with some additional complications. The first complication is just that it will simply take longer to build up sufficient TTSI capacity. Fortunately, lockdowns also suppress the virus, so while TTSI capacity is being built up, the number of active infections is also declining. Engaging the TTSI strategy for a fraction of cases before these lines cross will provide valuable experience and information, and will suppress the virus beyond what the lockdown alone achieves. After these lines cross, all active cases will be a part of the TTSI strategy and we should see a rapid decrease in new infections every week. More caution is required in opening up the economy in a red area because of the large number of active infections, so we recommend taking this week by week with every week of significant decline leading to another phase in the TTSI plan. Note here that the amount of contact tracing work is related to both economic activity (which increases the number of contacts) and the number of infections. Given this, we expect the exponential decline in active cases to rapidly enable the economy to open up without increasing the amount of active contact tracing work. Once the economy is fully opened up, further exponential declines will allow these trained contact tracers to get back to their normal jobs and form a reserve corps in case of further outbreaks.

Basis of Our Estimations

Our numbers are inferred by performing basic computations on estimated quantities. We give targets for a community to “suppress” the disease, which means to sustain TTSI to a point where community transmission is largely removed and where the dominant source of infections is people coming from the outside. After suppression, the next phase is “maintenance,” where the objective is to catch all new outbreaks arising from the outside.

Appendix: Further Discussion and Definitions

Basis of Our Estimations

Infection Fatality Rate (IFR)

The number of presently known infections is clearly a severe underestimate. We can get a better estimate from the infection fatality rate, or IFR, because deaths from COVID-19 are better known. South Korea has a case fatality rate of ~2%, but when one includes their likely number of suspected cases, the IFR estimate is ~1%, according to Wikipedia's article on the pandemic in South Korea. We use this estimate because it is the most trustworthy large-scale number, but there are others: Iceland's IFR is at .6%, and the Diamond Princess's IFR is at 1.8%. NYC's serotesting vs. fatality rate suggests an IFR of .7%. Altogether, 1% seems like a good infection fatality rate estimate, as long as health care is not overwhelmed.

IFR Adjustment by COVID Vulnerability Index (CCVI)

Different MSAs (or interconnected communities as discussed above) may have different IFRs due to various socioeconomic factors. Because of this, we have adjusted the IFRs based on the CCVI. Specifically, we use these estimates: IFR = .008 for the bottom 20% of the CCVI; IFR = .0125 for the top 20% of CCVI distribution; and IFR = .01 for the remainder.

The methodology for this is follows: The CCVI contains various socioeconomic and COVID-specific indicators of vulnerability. The CCVI integrates metrics directly from the established CDC Social Vulnerability Index (SVI), which links socioeconomic status, household composition and disability, minority status and language, and housing type and transportation as a composite score representative of populations disproportionately affected by and less resilient to disasters. In addition, two measures were added to the CCVI: (1) epidemiological factors, incorporating high-risk populations (those with underlying conditions), influenza and pneumonia death rates, and population density, and (2) health care system factors capturing the capacity, strength, and preparedness to respond to the health care needs of the respective population. We incorporated this index by conditioning the infection fatality

Appendix: Further Discussion and Definitions

Basis of Our Estimations

rate on the level of vulnerability expressed, drawing on research that shows correlation between fatality and sociodemographic variables ([Artiga et al., 2020](#)), as well as specifics ([Bohk-Ewald et al. 2020](#)) such as density ([Iype and Gulati, 2020](#)), hospital and medical capacity ([Onder et al. 2020](#)), and age ([CDC C-19 Response Team, 2020](#)).

Given the heterogeneity in these variables at the county/MSA level, we conducted a sensitivity analysis to the IFR value. Our analyses used 0.005, 0.010, and 0.015. These values are aligned with the mortality multiplier d_mult (as compared to the reference IFR from Hubei, China), to model the propagation of the SARS-CoV-2 epidemics in Florida, Georgia, and Mississippi. These methods build on previous work ([Bredderman and Messer, 2020](#); [Wilder et al. 2020](#)).

Tests to Detect One Positive

Estimates from South Korea at the peak of their outbreak suggest they needed to conduct about 25 tests to detect one positive case, so multiplying by the 25 tests/infection.

Tracers per New Case per Day (Team Size)

In order to succeed with testing, we need to ensure that we can find those at-risk contacts sufficiently fast before they can (unknowingly) go on to infect others. Here, the size of this workforce can be estimated using the approximate rule of “five contact tracers per new case per day.” The reason for this is that one tracer needs to do an interview (as soon as possible), and then a team of three people should spend the next twelve hours to try and find all those at risk and discuss with them how to take appropriate steps.

Reproduction number during TTSI (RTTSI)

During the effective TTSI, we use an upper bound that each infected person spreads the disease

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Appendix: Further Discussion and Definitions

Basis of Our Estimations

to at most five other people downstream (on average). In other words, we assume the reproduction number in TTSI is no more than 0.8, since $1 \div (1 - \text{RTTSl}) = 1 \div (1 - 0.8) = 5$. We view this as conservative estimate, and it can be readjusted appropriately.

Presymptomatic Infection Period

We will assume that the time when an infected person is unknowingly spreading the disease is upper bounded by five days, which we are taking as conservative estimate. It is plausibly closer to three days. After this time, we assume the person is not actively a spreader.

Maintenance Level Testing and Tracing

Once COVID-19 is suppressed and the economy and social functioning are largely back to normal, tests and tracing need to be performed in order to suppress any new outbreaks (e.g., people entering from a different region). This level of testing is crudely determined by the population of the region divided by 10,000. This was chosen to be equal maintenance levels currently used in South Korea (which are closer to one test per 10,000 people; see <https://ourworldindata.org/grapher/full-list-covid-19-tests-per-day?country=KOR>). This number can easily be refined with time. We assume that in maintenance we will also have one tracer per 20,000 people, again based on the Korean experience.

Computation and Estimates

The following discusses the computation and estimates that lead to our conclusions.

1. “new infections / day”: Due to the shortages in testing, confirmed positives from testing is not an accurate measure of estimated active cases. The number of deaths per day can give us an estimate of the number of active cases, by dividing by the IFR, which we take as ~1% (see above). Note that

Appendix: Further Discussion and Definitions

Computation and Estimates

deaths per day provide a lagging indicator, with about half occurring two weeks after infection. Therefore, it is a reasonably reliable as an upper estimate while fatalities are declining and not reliable when fatalities are growing. The new infections per day are the max of active cases $\div 7$ or (deaths last week) $\div 7 \div \text{IRF}$, where the (deaths last week) are the cumulative deaths from Johns' Hopkins data for the US county level (see <https://github.com/CSSEGISandData/COVID-19>). The numbers in the report correspond to the reported deaths and cases between April 28 and May 5.

2. “total number of presymptomatic cases”: The number of active cases spreading will be the (new infections / day) \times (presymptomatic period), which accounts for the new infections from the last few days who are still spreading the disease; this then results in the total number of individuals who are spreading the disease before they know they are infecting others.

3. “fast tests / day”: We seek to catch all new positives at a reliable rate. These are the number of “fast tests/day”. This is obtained by multiplying (new infections / day) \times (tests to detect one positive).

4. “total tests to suppression”: This is the total number of tests it takes to bring the community to a point where there is no active community spread. This equation will be determined by:

$$(\# \text{ presymptomatic cases in the community}) \times (\text{tests to detect a positive}) \div (1-\text{RTTSl})$$

Let us interpret each of these terms. The (# active spreaders in the community) is the same as the total number of pre-symptomatic cases. Dividing by (1-RTTSl) (or multiplying by 5 using our estimate above) accounts for the total number of downstream people that will be effected. Multiplying this by (test to detect a positive) gives us the total number of tests for suppression.

5. “slow tests / day”: This maintenance level of testing will be determined by the population size as: (population) \times (level of maintenance testing/person).

6. “total tests for a year”: This cumulative total includes both the total tests for suppression and the total slow tests for maintenance. In particular, this quantity is: (total tests for suppression) $+ 365 \times$ (slow tests per day)

7. “tracers/day “ (team size): This is (new infections/day) \times (tracers/new case per day) plus the sum of the maintenance level of tracers which is (population) \times (tracer/person).

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