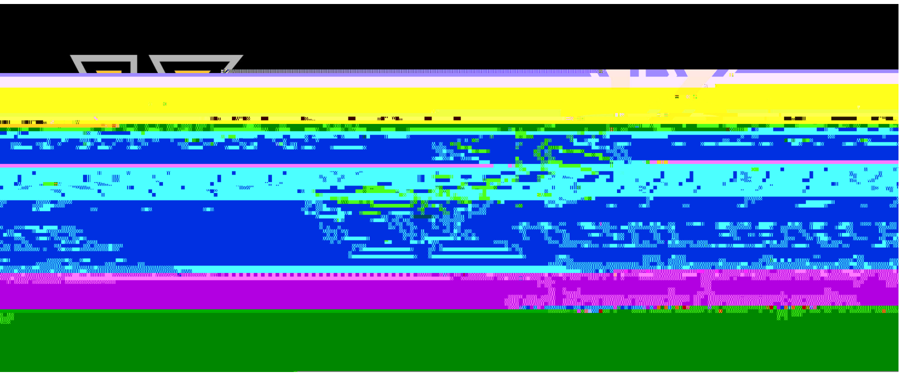

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Title:

"Is Mandatory Mass Testing for COVID-19 a Poor Policy?"

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Is Mandatory Mass Testing for COVID-19 a Poor Policy?

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Abstract

In this note I describe simple logic behind COVID-19 mass testing, which explains why any underlying policy is economically unsubstantiated. The application

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accuracy is still far below this number and cannot justify the underlying epiphenomenon costs.

One of the reasons why this apparently intuitive calculation usually remains under the shroud of ignorance is our own biology. The human brain has evolved to solve extraordinary complex tasks, which has bolstered the advancement of civilizations. However, as shown by numerous studies (De Martino et al. (2006), Bechara and Damasio (2005), Thaler and Ganser (2015) to name a few), despite its triumph in the realm of logic, the human brain is subject to numerous biases and pitfalls. Some are due to the neural link between the limbic system and the cortex (e.g. Floresco et al. (2008)), others stem from the specificity of wiring evolved as a byproduct of social exchange (e.g. Cosmides (1989)). The latter is a salient example of how human brains are not always capable of comprehending randomness and probabilities out of social context.

Interestingly, even people with specialized knowledge are not exempt from making those biases. For example, half a century ago, Casscells et al. (1978) surveyed residents of a prominent medical school asking the respondents the following question:

"If a test to detect a disease whose prevalence is one in a thousand has a false positive rate of 5 percent, what is the chance that a person found to have a positive result actually has the disease, assuming you know nothing about the person's symptoms or signs."

Almost half of the respondents answered 95% percent, and only 18% of the surveyed respondents answered correctly: 1.96%. The problem may be trivial after juxtaposing the numbers of false positives and true positives: for each 51 people out of a thousand who test positive (50 false positives as 5% from 999 and 1 true positive), only one will actually have the disease. However, our brains did not evolve to tackle such tasks, and that is why many people fail at this seemingly simple problem.

Of course, a more formal way to approach this question is by using Bayes' Theorem (Joyce (2003)), because conditioning on the positive test provides an additional piece of information and reduces the final sample space. In addition, its application also allows us to account for false negatives, which is an inescapable bane of medical testing.

Attesting to the results of this survey, Bennett (2009) notes that false positives are not human or lab errors, but rather a consequence of making tests sensitive to different deviations from a physiological norm. Reducing the false positive rate (FPR)

inevitably leads to an increase in false negatives. For any disease testing, the latter is more hazardous than the former, which prompts the designers to compromise on a larger number of false positives rather than false negatives.

As shown by different studies (e.g. Xiao et al. (2020), West et al. (2020) and Winichakoon et al. (2020)), current COVID-19 tests produce a substantial number of false negatives, which is an important problem from an epidemiological standpoint. However, much less attention is given to false positives, which may not be as crucial from a public health perspective, but are central to economic policies. This note addresses the viability of the latter.

2 Methodology

The accuracy of testing is directly linked to the number of false positives and false negatives which contaminate the sample. The former are described by the specificity of the test, and the latter by its sensitivity (Lalkhen and McCluskey (2008)). At this point, an efficient ubiquitous COVID-19 test simply does not exist. Different versions of the test offer various compromises between sensitivity and specificity.[1] On average, there seem to be around $5 - 10\%$ of false positives, so we will take 5% as our baseline case gradually decreasing it to 1%. To simplify things, let us also assume that the false negative rate (FNR) is 0. It is easy to see that the increase in FNR would negatively affect the conditional probability of testing positive for a person with the disease. Hence, with small values for FPR and FNR we would expect the tests to be quite reliable.

Consider a random person in the population who had no direct contact with infected people nor shows any symptoms of the disease. Let $P(S)$ be his prior probability of having COVID-19. Then $P(H) = 1 - P(S)$ is the probability of not having the disease. If $FNR = 0$, then the test always provides true positives. Hence, the conditional probability of the sick person to test positive is $P(P|S) = 1$. On the other hand, if $FPR = 5\%$, the conditional probability of testing positive when a person does not have the disease is $P(P|H) = 0.05$.

There are essentially two ways, in which this person could have tested positive. He either had COVID-19, and the test showed it correctly (true positive), i.e. $P(S \cap P) =$

[1] The Foundation for Innovative New Diagnostics (FIND) provides comparisons of some of the tests on their official website: https://www.finddx.org.

$P(S)P(P|S)$, or he did not have the disease, and tested positive (false positive), i.e. $P(H \cap P) = P(H)P(P|H)$. The marginal probability that he tested positive is the union of two independent events: $P(P) = P(S \cap P) + P(H \cap P)$. Then, after testing positive, the following inverse probability defines how likely it is that he tested positive due to having the disease:

$$P(S|P) = \frac{P(S \cap P)}{P(P)} = \frac{P(S)P(P|S)}{P(S)P(P|S) + P(H)P(P|H)} \tag{1}$$

Notice that $P(S|P)$ is increasing in $P(S \cap P)$, because the latter term is simultaneously in the numerator and the denominator. Since $P(S \cap P)$ decreases with an increase in FNR, the whole posterior probability also decreases. The above equation is Bayes' Theorem, which effectively relates the probability of following one of the paths to the constrained sample space defined only by the paths that could lead to the observed outcome. In our context it shows the likelihood of having tested positive due to actually having the disease rather than being a false positive observation.

3 Results

To compute (1) we only need to know the prior unconditional probability that a randomly chosen person without symptoms or previous direct contact with infected people has COVID-19. We can put a bound on these numbers from publicly available information. As of June 03, 2020, in the USA, there was an average of $5{,}718$ confirmed cases per one million people. Hence, the probability that a randomly chosen person has the disease is $P(S) = \frac{5{,}718}{1{,}000{,}000} \approx 0.57\%$.[2] Correspondingly, the probability of not having the disease is $P(H) = 1 - P(S) = 99.43\%$. Because we already know $P(P|S$6)9S 1 assumed probabilities), the likelihood of actually having COVID-19 after testing positive is only 10.32%. The above number tells us that even if the test has high specificity (5% of false positives), it does not produce accurate results when the infection rate is very small, which is the case for all countries in the world. Even within almost laboratory conditions characterized by $FPR = 1\%$ and $FNR = 0$, the resulting probability rises only to 36.51%. It effectively renders the test useless for a person who does not have any symptoms and did not have direct contact with infected people. The probability further decreases if the test is also prone to false negatives. For example, assuming $FNR = 10\%$, the conditional probability of testing positive while having COVID-19 is now less than 1, which further decreases the examined inverse probabilities:

$$P(S|P) = \frac{0.0057 \times 0.9}{0.0057 \times 0.9 + 0.9943 \times 0.05} = 9.38\% \quad \text{when } FPR = 5\%$$

$$P(S|P) = \frac{0.0057 \times 0.9}{0.0057 \times 0.9 + 0.9943 \times 0.01} = 34.11\% \quad \text{when } FPR = 1\%$$

The tests would be more accurate if the infection rate was higher, which may be achieved by looking at certain regions within counties. The results for each U.S. state are presented in Table 1. The numbers outside the parentheses represent $P(S|P)$ when there are no false negatives, and the numbers inside the parentheses show the corresponding probabilities when $FNR = 10\%$. Despite that probabilities only for 7 states (CT, DE, DC, MA, NJ, NY, and RI) cross the “flip of a coin” threshold of 50% (when $FPR = 1\%$), COVID-19 tests with low FNR and FPR are extremely unlikely in reality. Hence, assuming that the test results are independent of each other, a random person would need to test positive four times in the state of New Jersey to make sure that he actually has the disease, while in a state like Montana this number skyrockets to 100 times!

Unless multiple testing is done, it is impossible to say whether a random person without symptoms or previous contact with infected people has COVID-19. The number of times the test needs to be performed varies from one state to another, and also hinges on dependence or independence of test results. By obvious reasons the necessity of multiple testing substantially inflates its cost. On the other hand, if the test is performed only once or even twice, its results are effectively useless. If a random person still decides to undergo testing and pays for it from his pocket, he makes an individual decision weighing associated benefits and costs (given that he understands

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Table 1: Percentage Probabilities of Having COVID-19 Conditional on Testing Positive

False Positive Rate (FPR)	5%	4%	3%	2%	1%
USA Total	10.31 (9.38)	12.56 (11.45)	16.08 (14.71)	22.33 (20.55)	36.51 (34.10)
Alabama	7.16 (6.49)	8.80 (7.99)	11.39 (10.37)	16.17 (14.79)	27.84 (25.78)
Alaska	1.36 (1.22)	1.69 (1.52)	2.24 (2.02)	3.33 (3.01)	6.45 (5.85)
Arizona	5.77 (5.22)	7.11 (6.44)	9.26 (8.41)	13.27 (12.11)	23.44 (21.60)
Arkansas	4.93 (4.46)	6.09 (5.52)	7.96 (7.22)	11.49 (10.46)	20.62 (18.94)
California	5.64 (5.11)	6.96 (6.31)	9.07 (8.24)	13.02 (11.87)	23.04 (21.22)
Colorado	8.54 (7.75)	10.46 (9.51)	13.47 (12.29)	18.94 (17.37)	31.85 (29.60)
Connecticut	19.61 (18.00)	23.37 (21.54)	28.91 (26.79)	37.89 (35.44)	54.95 (52.33)
Delaware	16.76 (15.35)	20.11 (18.47)	25.13 (23.20)	33.49 (31.19)	50.18 (47.55)
District Of Columbia	20.55 (18.89)	24.44 (22.55)	30.13 (27.96)	39.28 (36.80)	56.40 (53.80)
Florida	5.20 (4.70)	6.41 (5.81)	8.37 (7.60)	12.06 (10.98)	21.52 (19.80)
Georgia	8.35 (7.58)	10.23 (9.30)	13.19 (12.03)	18.56 (17.02)	31.32 (29.10)
Hawaii	0.91 (0.82)	1.13 (1.02)	1.51 (1.36)	2.25 (2.03)	4.40 (3.98)
Idaho	3.18 (2.87)	3.94 (3.56)	5.19 (4.69)	7.59 (6.88)	14.11 (12.88)
Illinois	16.37 (14.98)	19.66 (18.05)	24.60 (22.70)	32.86 (30.58)	49.46 (46.83)
Indiana	9.63 (8.75)	11.76 (10.71)	15.09 (13.79)	21.05 (19.35)	34.78 (32.43)
Iowa	11.32 (10.30)	13.76 (12.56)	17.54 (16.07)	24.19 (22.31)	38.96 (36.49)
Kansas	6.57 (5.95)	8.08 (7.33)	10.49 (9.54)	14.95 (13.66)	26.02 (24.04)
Kentucky	4.37 (3.95)	5.40 (4.89)	7.07 (6.41)	10.25 (9.32)	18.60 (17.05)
Louisiana	15.14 (13.84)	18.24 (16.72)	22.93 (21.12)	30.86 (28.65)	47.16 (44.55)
Maine	3.47 (3.14)	4.31 (3.89)	5.66 (5.12)	8.26 (7.50)	15.27 (13.95)
Maryland	15.50 (14.17)	18.66 (17.11)	23.42 (21.58)	3 0 0BT185.215942 019.963 lSQBT185.217 475.087 Td[(11.32)-4114.17)(Io)31.Ma	