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Title:

"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 of basic probability theory shows that unless the testing accuracy is close to a hundred percent, even a small number of false positives introduces significant bias into random tests making them extremely unreliable.

Keywords: COVID-19; Medical Testing; Public Policy

JEL Codes: I18, H51

1 Introduction

This note is motivated by recent proliferation of debates in many countries concerning the implementation of mandatory mass testing for COVID-19, which would be administered by the governments and effectively financed by taxpayers' monies. In a more lenient agenda, it is at least supposed that private and state enterprises would be compelled to perform mass testing of their employees. In this note I turn to the basic logic of medical testing and argue the futility of such policies. When the infection rate is low, for a random person not exhibiting any symptoms of the disease or having engaged in close contact with infected people, the predictive power of the test even with 99%

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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 $P(P|S)$ and $P(P|H)$, it is straightforward to calculate the likelihood of that person being sick if he tested positive:

$$P(S|P) = \frac{0.0057}{0.0057 + 0.9943 \times 0.05} = 10.32\%$$

That is, if a person living in the USA had no reason to suspect having COVID-19 and were randomly tested, and the results of the test came back positive (under the

[2] Note that this probability is based only on the confirmed cases, while in reality the infection rate may be higher.

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 the associated probabilities). In this case, he should be allowed to do it voluntarily unless the tests' capacity is constrained. However, any policy compelling every person to test for COVID-19 has no economic foundation, because the costs will surely outweigh the benefits of multiple testing. In the end, it does not even matter who is incurring the costs: government, private enterprises or consumers — social welfare will decrease.

The situation would be different if, for example, someone had direct contact with an infected person. Then, it is effectively a flip of a coin whether this person got infected or not. When the prior probability rises to 50%, the examined inverse probabilities increase dramatically, and the associated percentages match the accuracy of the tests. For example, for the USA, when $P(S) = 50\%, FNR = 0$ and $FPR = 5\%$ it follows that $P(S|P) = 95.24\%$, which is nine times higher than the initial 10.32%. Thus, testing is more likely to be efficient for anyone who has symptoms or had contact with an infected person.

4 Conclusion

In this note I examined the feasibility of COVID-19 mass testing policies using simple logic of medical testing hinging on their sensitivity and specificity. Using the USA as the example, I showed that mass testing has questionable economic foundation even for the states with the highest infection rates unless the accuracy of COVID-19 tests approaches 100%. Since the latter is not feasible, testing should be done exclusively on a voluntary basis for people who are ready to pay for them given the available capacity.

Because multiple testing is required to make sure that a randomly selected person actually has the disease, it creates substantial strain on testing capacity and the associated costs. While the benefits of multiple testing remain uncertain, the costs are real and rise substantially for the regions with low infection rates.

References

Bechara, A. and A. R. Damasio (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and economic behavior 52*(2), 336–372.

Bennett, D. J. (2009). *Randomness*. Harvard University Press.

Casscells, W., A. Schoenberger, and T. B. Graboys (1978). Interpretation by physicians of clinical laboratory results. *New England Journal of Medicine 299*(18), 999–1001.

Cosmides, L. (1989). The logic of social exchange: Has natural selection shaped how humans reason? studies with the wason selection task. *Cognition 31*(3), 187–276.

De Martino, B., D. Kumaran, B. Seymour, and R. J. Dolan (2006). Frames, biases, and rational decision-making in the human brain. *Science 313*(5787), 684–687.

Floresco, S. B., J. R. S. Onge, S. Ghods-Sharifi, and C. A. Winstanley (2008). Cortico-limbic-striatal circuits subserving different forms of cost-benefit decision making. *Cognitive, Affective, & Behavioral Neuroscience 8*(4), 375–389.

Joyce, J. (2003). Bayes' theorem.

Lalkhen, A. G. and A. McCluskey (2008). Clinical tests: sensitivity and specificity. *Continuing Education in Anaesthesia Critical Care & Pain 8*(6), 221–223.

Thaler, R. H. and L. Ganser (2015). *Misbehaving: The making of behavioral economics*. WW Norton New York.

West, C. P., V. M. Montori, and P. Sampathkumar (2020). Covid-19 testing: the threat of false-negative results. In *Mayo Clinic Proceedings*. Elsevier.

Winichakoon, P., R. Chaiwarith, C. Liwsrisakun, P. Salee, A. Goonna, A. Limsukon, and Q. Kaewpoowat (2020). Negative nasopharyngeal and oropharyngeal swabs do not rule out covid-19. *Journal of clinical microbiology 58*(5).

Xiao, A. T., Y. X. Tong, and S. Zhang (2020). False-negative of rt-pcr and prolonged nucleic acid conversion in covid-19: Rather than recurrence. *Journal of Medical Virology*.

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)	31.45 (29.22)	47.85 (45.23)
Massachusetts	22.95 (21.14)	27.13 (25.10)	33.17 (30.88)	42.68 (40.13)	**59.83** (57.27)
Michigan	10.46 (9.51)	12.74 (11.62)	16.30 (14.91)	22.61 (20.82)	36.88 (34.47)
Minnesota	8.43 (7.65)	10.33 (9.39)	13.31 (12.14)	18.72 (17.17)	31.54 (29.31)
Mississippi	9.93 (9.02)	12.11 (11.03)	15.52 (14.19)	21.61 (19.88)	35.54 (33.16)
Missouri	4.36 (3.94)	5.39 (4.88)	7.06 (6.40)	10.23 (9.30)	18.57 (17.03)
Montana	0.97 (0.87)	1.21 (1.09)	1.61 (1.45)	2.39 (2.16)	4.68 (4.23)
Nebraska	13.21 (12.04)	15.98 (14.62)	20.23 (18.58)	27.56 (25.51)	43.21 (40.65)
Nevada	5.49 (4.97)	6.77 (6.14)	8.83 (8.02)	12.69 (11.57)	22.53 (20.74)
New Hampshire	6.55 (5.93)	8.05 (7.31)	10.46 (9.51)	14.91 (13.62)	25.95 (23.98)
New Jersey	27.27 (25.24)	31.92 (29.67)	38.46 (36.00)	48.39 (45.77)	**65.22 (62.79)**
New Mexico	7.13 (6.46)	8.76 (7.95)	11.35 (10.33)	16.11 (14.73)	27.75 (25.69)
New York	28.64 (26.54)	33.41 (31.11)	40.08 (37.58)	**50.09** (47.46)	**66.74 (64.37)**
North Carolina	5.59 (5.06)	6.89 (6.25)	8.99 (8.16)	12.90 (11.76)	22.86 (21.05)
North Dakota	6.58 (5.97)	8.10 (7.35)	10.52 (9.56)	14.99 (13.69)	26.07 (24.09)
Ohio	5.94 (5.38)	7.32 (6.63)	9.52 (8.65)	13.64 (12.44)	24.01 (22.14)
Oklahoma	3.33 (3.00)	4.12 (3.73)	5.43 (4.91)	7.93 (7.19)	14.69 (13.42)
Oregon	2.04 (1.84)	2.54 (2.29)	3.36 (3.03)	4.96 (4.48)	9.45 (8.58)
Pennsylvania	10.89 (9.91)	13.25 (12.09)	16.92 (15.49)	23.41 (21.57)	37.93 (35.49)
Rhode Island	22.59 (20.80)	26.72 (24.71)	32.72 (30.44)	42.18 (39.63)	**59.33 (56.77)**
South Carolina	4.61 (4.16)	5.69 (5.15)	7.45 (6.76)	10.78 (9.80)	19.46 (17.86)
South Dakota	10.50 (9.55)	12.79 (11.66)	16.36 (14.97)	22.68 (20.89)	36.98 (34.56)
Tennessee	6.80 (6.16)	8.35 (7.58)	10.84 (9.86)	15.42 (14.10)	26.73 (24.71)
Texas	4.49 (4.06)	5.56 (5.03)	7.28 (6.60)	10.53 (9.58)	19.06 (17.49)
Utah	6.00 (5.43)	7.39 (6.70)	9.61 (8.73)	13.76 (12.56)	24.19 (22.31)
Vermont	3.08 (2.78)	3.82 (3.45)	5.03 (4.55)	7.36 (6.67)	13.71 (12.51)
Virginia	9.95 (9.04)	12.13 (11.05)	15.55 (14.21)	21.64 (19.91)	35.58 (33.21)
Washington	5.79 (5.24)	7.13 (6.47)	9.29 (8.44)	13.32 (12.15)	23.52 (21.67)
West Virginia	2.26 (2.04)	2.81 (2.53)	3.71 (3.35)	5.47 (4.95)	10.37 (9.43)
Wisconsin	6.26 (5.67)	7.71 (6.99)	10.02 (9.11)	14.32 (13.07)	25.05 (23.12)
Wyoming	3.06 (2.76)	3.79 (3.42)	4.99 (4.52)	7.31 (6.63)	13.63 (12.43)

Notes: The numbers in the table represent the probabilities of having COVID-19 conditional on positive test. Each column provides values for different FPR when false negative rate (FNR) is zero. Numbers in the brackets are calculated for the same FPR, but when $FNR = 10\%$. Numbers in bold are probabilities higher than 50%.