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Increasing Lab Capacity for Covid-19 Viral Testing

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Abstract

I study how to increase the capacity to test for Covid-19 with the two-swabs group testing strategy. It consists in bunching first swabs in groups and processing the second swabs individually only in case the group result is positive. Using a simulation, I derive multipliers of the lab capacity in worse case scenario that indicate how many more tests a lab can be sure to perform each day. The results show that the gains can be substantial even in case the actual fraction of positive tests is bigger than the expected fraction used to set the optimal group size.

JEL classification: E1, I1, H12.

Keywords: Group, Test

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1 Introduction

The RT-PCR (Real Time Polymerase Chain Reaction) test on a nasopharyngeal swab is the most reliable way to diagnose for a Covid-19 infection. Due to the big number of asymptomatics, it is absolutely crucial to test as many individuals as possible in order to isolate the infected and reduce contagions. However processing a big number of test is costly and time consuming and the laboratories do not always have the resources and infrastructure to do so. The result is an insufficient number of quarantined asymptomatics and an epidemic that spreads quickly, leaving policy makers without many options aside from a lockdown. Moreover, waiting longer to take a test or to receive its result is also extremely costly for the individuals that cannot work or send their children to school.

In this paper I study how to increase the lab capacity to process tests with the group testing strategy of Dorfman (1943). The idea consists in taking two samples from each individual using two swabs. The first sample is mixed with others and processed in groups of fixed size. If the result is negative for the group, then all of the group members are negative. The second swabs are discarded. A positive result for the group means instead then at least one of the components is positive. In this case the second swabs are processed individually to identify all positives. In all cases, the result is a perfect identification of all positives without classification errors. Israel and the state of Nebraska are, to date, the only two examples of application of this testing protocol to Covid-19 (Gollier and Gossner 2020).

The optimal group size that minimizes the total number of tests is a decreasing function of the fraction of positive individuals in the tested population. If, on average, 1.5% of the tests are positive, testing in groups of 11 allows to reduce the number of tests, on average, by a factor of 4. In other words, for fixed laboratory capacity, it is possible to process, on average, 4 times as many tests. I will refer to this number as the *Lab Capacity Multiplier* (LCM). If instead 3% of the tests are positive, testing in groups of 6 yields a LCM of 3.

These gains in lab capacity implied by the computations by Dorfman (1943) are theoretical averages, which are different from what a lab can actually achieve on a day-by-day basis. In practice it is possible that it would not be able to process that many test if, as a result of sampling variability, there are positives scattered in many groups, so that individual tests are

required frequently. Leftovers tests can be actually processed the next day and, on average, there will be enough capacity to do so, but it will take longer to receive the test response, with a high cost for the quarantined individuals waiting for a result. I perform a simulation exercise to show that there can be substantial gains even in case the lab capacity is set to the worse case scenario. If the expected fraction of positives is 1.5%, the worse case scenario multiplier of the lab capacity is equal to 2.75. Translated, a lab that adopts the two-swabs strategy can be sure to process 2.75 as many tests as before without leftovers, so that everybody will receive an answer the same day.

A second problem is that the gains from the two swabs strategy are smaller if the actual fraction of positive tests is bigger than the expected capacity according to which the lab sets the optima group size. In other words, a lab that sets its capacity according to the theoretical LCM might have many leftover tests in case of more positives than expected, which is likely to happen when the pandemic accelerates or right after a lockdown. Simulation results show however that there can be gains even in case of a significant mistake. For instance, for an expected positive fraction of 1.5%, the tests are reduced, on average, by a factor of 2 even if the actual fraction of positives is 5%, or more than three times as big as expected. In this case the lab can be sure to process roughly 1.6 times as many tests every day.

Another related problem is that the economic convenience of the two-swabs strategy depends upon the ratio of the cost of testing device (i.e. the swab) to the processing cost (PCR test). The strategy works better in case this ratio is small, since it entails using two devices for each tested individual. I show that there are gains even in case of a high cost ratio if the expected fraction of positives in the tested population is small.

The two swabs strategy can be generalized to three swabs with two levels of grouping. I show that this strategy, while being slightly more complicated to implement, might actually increase the LCM even more, although the costs will be high even in case of a relatively small cost ratio.

The idea of the two-rounds group testing strategy is due to Dorfman (1943). More generally, there is a huge literature on the mathematics of group testing. Alridge, Johnson and Scarlett (2019) survey the most important contributions. In the context of Covid-19, Gollier and Gossner (2020) study group testing applications targeted at estimating the virus preva-

lence, at allowing negatives to return to work and at screening for positives. My contribution is limited to the screening of positives and consists in producing simulation results to help labs setting their capacity in a such a way to produce quick responses.

The rest of the paper is organized as follows. Section 2 describes the two-samples strategy by Dorfman (1943) and its theoretical results, extending also the analysis to the cost of the tests. Section 3 summarizes the main results from the simulation exercise. Section 4 discusses two extensions, to groups of different size and two a three-swabs strategy. Section 5 concludes.

2 The Two Swabs Strategy

In this section I describe the original idea by Dorfman (1943), focusing the analysis on the increased lab capacity and extending it to the cost of the tests.

Suppose that the tests are performed on a population of size n and that the percentage of positives is π. Two samples are collected from each individual using two swabs. The first samples are grouped in groups of fixed size g. For simplicity, suppose that the population size is such that n/g is integer. The tests are performed sequentially by a single lab and there is independence in the results, meaning that there are no clusters of infected that are processed back-to-back. The result of the group test is negative if all of the group members are negative. This happens with probability $(1-\pi)^g$. In this case the lab performs 1 test only for g individuals and discards the second swabs. A positive group test results means instead that at least one of the group components is positive. This happens with probability $1-(1-\pi)^g$. In this case the lab needs to use the second swabs to perform g individual tests, which amounts to a total of $g+1$ tests for g individuals. Given that there is a total of n/g groups, the expected number of tests performed is equal to:

$$nT(\pi, g) = \frac{n}{g}\left\{(1-\pi)^g + (1+g)[1-(1-\pi)^g]\right\} \tag{1}$$

The optimal test size is the value of g that minimizes[1] T for fixed π. This is the original

[1]The number of tests n does not play a role in the minimization problem as long as it is divisible by g (n/g is integer). If it is not, than the expected number of test is slightly different than the output of equation 1 and the solution to the problem entails also an additional strategy to test the leftovers individuals. For instance, suppose that there are 100 individuals to test. Forming groups of 8 yields 12 full groups plus 1 remainder group of 4, with three possible additional strategies for the 4 leftovers: 4 individual tests, 2 groups of 2 or 1

problem solved by Dorfman (1943). I will focus on integer values of g in order to have simpler strategies as a result (I discuss the non-integer case in section 4). At the optimal group size $g^*(\pi)$, a total of $nT^*(\pi)$ tests are required to perfectly screen n individuals.

A minimum number of tests per individual $T^*(\pi)$ means that a lab can process more tests with the same maximum capacity. I define the expected Lab Capacity Multiplier (LCM) as the ratio between the number of test that would be performed in case of an individual testing strategy n to the expected number of tests performed under the two-swabs strategy for the optimal choice of the test size: $LCM = n/T^*(\pi)$. For instance, $T^*(\pi) = 0.5$ means that a lab adopting the two-swabs strategy can perform, on average, twice as many tests than it would otherwise do in case of individual testing.

The left panel of figure 1 plots the optimal group size for $0.001 \leq \pi \leq 0.1$; the right panel of figure 1 plots instead the expected LCM for the same values of π. The results for selected levels of π are also summarized in table 1, alongside the number of tests required to screen $n = 100$ individuals. The bigger the expected fraction of positives, the smaller the group size, since it is actually more likely to find a positive among the group. The expected number of tests is therefore an increasing function of π, while the expected capacity multiplier decreases with π. If the expected fraction of positives is 1%, the optimal test size is 11 and the expected number of tests is 19.56 for each 100 individuals. This means that the lab can process slightly more than 5 times as many tests with the same capacity upon adoption of the two-swabs strategy. If the expected fraction of positives is instead 3%, the optimal group size is 6, the expected number of tests per 100 individuals 33.37 and the LCM close to 3. In case π is 10%, the optimal group size is just 3 tests, the expected number of tests 59.39 per 100 and the expected LCM is only 1.68. In other words, the two-swabs strategy is not worthwhile implementing in case of high incidence of the infection in the tested population.

Dorfman (1943) did not consider explicitly the the cost of this testing strategy. Putting it differently, the assumption behind its analysis is that the only reason why the labs were not able to process tests is either a time constraint or the luck of testing devices (such as reagents). However cost monitoring is crucial in case there is a fixed amount of resources assigned to each lab or, for public health systems, in case of limited borrowing capacity by

group of 4. In the spirit of the analysis, I assume that the number of individuals to test is fixed in multiples of g after the optimal test size is computed.

the government. Moreover, the two-swabs strategy entails consuming two testing devices per individual, which means that it is worthwhile implementing only if the cost of the device (the swab) c is sufficiently smaller than the processing cost (PCR test) C. Actually different labs and/or governments can face different costs as a consequence of different physical infrastructure, technology, workforce size and organization and as a consequence of the different market prices for the reagents or of the products needed to produce them in case of in-house production. Moreover, it is in principle possible to have important cost fluctuations even within small time intervals, for instance if speculators try to take advantage from the onset of the epidemic. For all these reasons, it is important to compare testing strategies at different values of the underling costs. The total cost of performing individual tests on n individuals is $n(C+c)$. The total cost of the two-swabs strategy[2] is instead $n[T^*(\pi)C+2c]$. Denoting with $\bar{c}=c/C$ the ratio between the device cost and the processing cost, the relative expected cost S of the two-swabs strategy is therefore equal to:

$$S(\bar{c})=\frac{T^*(\pi)+2\bar{c}}{1+\bar{c}} \tag{2}$$

Table 2 reports this relative expected cost of the two-swabs strategy as a function of $\bar{c}$ for two levels of π, respectively 1.5% and 3%. The smaller is $\bar{c}$, the more convenient is the two-swabs strategy. For instance, if $\bar{c}$ is equal to 10%, the relative cost of the two-swabs strategy is roughly 40% if $\pi=1.5\%$ and 48% if $\pi=3\%$. If instead $\bar{c}$ is 50%, the relative expected cost of the two-swabs strategy is 82% in case of $\pi=1.5\%$ and 89% in case of $\pi=3\%$. Summarizing, the two-swabs strategy reduces the overall cost of the tests in case the device cost is much smaller than the processing cost and in case of small incidence of the infection in the population.

3 Simulation

The expected capacity multipliers in section 2 are theoretical averages that are different from what a lab can actually process each day, which depends on how many actual positives there

[2]Note that the optimal group size g that minimizes the number of tests is also the one that minimizes the cost of administering the tests.

are and how they are combined in groups. In particular, If most positives are bunched together in few groups, the lab will be able to process more. Conversely, if the positives are scattered across groups, second tests will be more frequent and the lab will be able to process less tests. Sampling variability might therefore induce a relevant problem for a lab: if it collects samples from $n \cdot LCM$ individuals (having a capacity of n individual tests per day), it might not be able to process all of them in the same day. Leftovers can be processed the following days and, on average, there will be enough capacity to do so, but the cost will be having longer and uncertain test response times.

In this section I propose a simulation exercise that shows the distribution of the gains from a two-swabs strategy for a particular choice of the probability π. I will use the simulation results to identify the smallest possible gains in the worse case scenario, which can help a lab set its maximum capacity to a number of tests that it will be sure to process each single day.

The details of the simulation are quite simple. I fix $\pi = 1.5\%$ as in Italy at the end of August. The corresponding optimal test size is $g = 9$. I fix the device to processing cost ratio to $\bar{c} = 0.1$ (the device costs is equal to one tenth of the processing cost). I simulate 5 thousand times the tests for a population of $n = 999$ individuals. The size of each simulation run is such that the ratio n/g is integer in order to have groups of equal size and to avoid dealing with leftover tests bunched in a smaller residual group. At each simulation round, I draw a random vector of n elements from a Bernoulli distribution with success probability equal to π. I therefore assume that the tests are on a random sample of the population and that there are no clusters of infected. Alternatively, the assumption is that there is a sufficiently big number of tests processed by the lab and that the samples are shuffled so that, say, samples from two family members that go together to take a test are not processed back to back[3]. At each simulation run, I compute the number of performed test, the lab multiplier and the total cost.

Figure 2 plots the empirical distribution of the lab capacity multiplier and of the total cost over all simulation runs. The extreme values are not discarded in the spirit of the exercise. The distribution is symmetric and the mean is very close to the expected LCM computed in section **??**: the median LCM is 4.219 and the mean 4.210. The interquartile range of the

[3]If there were clusters, the two-swabs strategy would work even better, since there would be many positives bunched together in groups, but I am ignoring this possibility to keep the analysis simple.

LCM is [3.92; 4.57], stressing that in a great number of cases the actual multiplier is close to its theoretical value. But there are also cases when the LCM turns out to be smaller: in 10% of the simulations, it is actually lower than 3.55. In 1% of the simulations, it is lower than 3.14. The worse case scenario is a LCM of 2.69. This actually means that, for $\pi = 1.5$, the lab will be sure to process 2.69 times as many tests as before upon adoption of the two-swabs strategy. Actually if it accepts 3 times as many tests, it will have leftovers in less than 1% of the days. As for the cost, the worse case scenario is 52% of the individual testing strategy. The cost will actually be bigger than 43% in less than 10% of the days and less than 39% in half of the days. A huge saving indeed.

Another problem associated with the two-swabs strategy is that the optimal group size is contingent on the expected fraction of positives. If the actual fraction of positives turns out to be higher than what is used to set the group size, there will be lower gains both in terms of additional tests performed and costs. I use again a simulation to gauge the extent of the problem and to help labs sets their capacity. Table 3 reports the results for two levels of expected π, respectively 1.5% (optimal test size 9) and 2% (optimal test size 8), and for an actual percentage of positives $\hat{\pi}$ between 0.5% and 5%. Again extreme simulation results are not discarded. The way to read the table is the following. Suppose that the lab expects to find $\pi = 1.5\%$ of positives and, accordingly, that it forms groups of 9. If it doubles its capacity, it is sure to process all of them if the actual percentage of positives $\hat{\pi}$ is below 3% (the worse case scenario multiplier for 3% expected positives is 1.97). If the actual positives turned out to be more than 3%, then the lab would face a small chance of not being able to process some of them. As for the budget, there is actually a bigger chance to exceed it, but since the median cost is smaller than 60% if the true π is below 5 percent, there is ample margin to compensate.

If however the lab gets the percentage right ($\pi = \hat{\pi}$), it can safely increase the capacity up to 4 times. Thus it is very important to have a good forecast model, updated daily, to predict the number of positives based on the diffusion pattern of the pathogen. The group size must be adjusted every day accordingly[4].

[4]Actually It is unlikely to have big swings in the number of positives from one day to next, unless there is a regime change such as the relaxation of some mitigation policy previously implemented.

4 Extensions

In this section I discuss two extensions. The first entails groups of different size, slightly more difficult to implement. The second is instead the possibility of using three swabs rather than two. In both cases I will show that such complicated strategies do not significantly improve upon the two-swabs strategy with equal group sizes.

4.1 Groups of Different Size

Dorfman (1943) solves for groups of equal size, which yields easier strategies to implement. But looking at easier strategies is meaningful only if the gains from more complex one are not too big. In this section I consider solution with different group sizes in order to understand if there are potential gains from their implementation. In particular, I consider the possibility of constructing H types of groups, each with g_i elements and such that $g_i \neq g_j$ if $i \neq j$. Denoting with h_i the fraction of groups of size g_i, the average group size is $\bar{g} = \sum_{i=1}^{H} h_i\, g_i$. For instance, an average group size of $\bar{g} = 5.5$ can be reached with $g_1 = 5$, $g_2 = 6$ and $h_1 = h_2 = 0.5$. An average group size of $\bar{g} = 3.33$ with $g_1 = 3$, $g_2 = 4$, $h_1 = 2/3$ and $h_2 = 1/3$. In both cases, the number of individuals to test is set after the choice of the group size in such a way that $n/\bar{g}$ is integer. The total number of tests is:

$$nT\big(\pi, H, \{g_i\}_{i=1}^{H}\big) = \sum_{i=1}^{H} h_i \frac{n}{g_i} \left\{ (1-\pi)^{g_i} + (1+g_i)[1-(1-\pi)^{g_i}] \right\} \tag{3}$$

The goal is to find a minimum with respect to g_i, h_i and H. Such a problem is very complicated to solve without imposing some more structure and/or without restricting the set of candidate solutions. To simplify it, I will look only at candidate solutions with the following characteristics: two types of groups only ($H = 2$), average group sizes in half integers $(1.5, 2.5, 3.5, \dots)$ or thirds of an integer $(1.33, 2.33, 3.33, \dots)$ and a difference between the two group sizes equal to 1 ($\Delta g = g_1 - g_2 = 1$). Both examples discussed at the beginning of this section meet these three requirements. Once again, the requirements are such that the resulting strategies are easy to implement. The results shows that there are no actual gains in adopting such strategies: the expected number of tests in case of groups of equal size is

always lower, albeit just slightly in some cases. Given that strategies with equal group sizes are arguably easier to manage, the conclusion is that it is better to focus on them. These arguments in do not exclude the possibility that some more complicated strategy, say with 3 or 4 different group size, might actually yield a smaller expected number of tests. But the overall test planning and group allocation problem will be much more difficult in case of a bigger number of groups H, especially if the average group size must be updated on a daily basis according to the evolution of the probability π. All in all, focusing on groups of equal size seems preferable.

4.2 Three Swabs

The two-swabs strategy is able to reduce the number of tests required to perfectly screen a given population. However using two swabs is not the only possibility. In principle, three, four or even more swabs can be used, bunching the tests in groups of progressively smaller size. The convenience of such strategies, abstracting from their complexity of implementation, depends mostly on two aspects: the expected fraction of positives and the relative magnitude of the device cost. The bigger the expected number of positives and the bigger the relative cost of the device, the less convenient they are, since they involve bigger group sizes at earlier stages and since they require using a lot of devices. In what follows, I consider a simple extension of the Dorfamn (1943) problem to a three-swabs strategy and compare its performance to the two-swabs case.

The three swabs strategy entails two separate rounds of bunching. Three samples must be collected for each tested individual. The first samples are merged into groups of size G. In case the group result is negative, which happens with probability $(1-\pi)^G$, the second and third samples are discarded and one test is necessary for G individuals. In case the group result is instead positive, which happens with probability $1-(1-\pi)^G$, the second samples are merged into G/g groups of size g and such that $1 \leq \mathrm{g} \leq \mathrm{G}$. At this stage we have the same problem discussed in section 2. The expected number of tests is equal to:

$$nT_3(\pi, g, G) = \frac{n}{G}\left\{(1-\pi)^G + \left[1-(1-\pi)^G\right]\left[1+\frac{G}{g}T(\pi, g)\right]\right\} \tag{4}$$

where $T(\pi, g)$ is defined in equation (1). The problem is now to find the values of G and

g that minimize T_3 for given level of π. As in section 2, I look only at integer values of G. For consistency, and given the results in section 4.1, I only look for solutions with integer values of G/g. For instance, for G is equal to 10, I only look at two values of g, 5 and 2. For the same reason, I do not consider prime numbers as candidate solutions for G.

The expected number of test with the three-swabs strategy is much lower. If the expected number of positives is 1.5%, a first groups size of G=18 tests and a second group size of g=9 tests make it possible to test 100 individuals with just 11.23 tests on average, with an expected lab capacity multiplier equal to 8.9. For a much higher number of positives, say 5%, the gains are smaller: with G=10 and g=10, the expected number of tests is 27.1 and the expected lab multiplier 3.68. The relative cost with respect to the individual testing strategy is:

$$S_3(\bar{c}) = \frac{T_3^*(\pi) + 3\bar{c}}{1 + \bar{c}} \tag{5}$$

where $T_3^*(\pi)$ is the minimum test number corresponding to the optimal choice of G and g. Figure 3 plots the costs associated with the two-swabs and with the three swabs strategies as a function of $\bar{c}$ for two levels of π, respectively 1.5% and 3%. For $\bar{c}$ between 10% and 20%, the two costs are very close. The costs diverge instead for higher $\bar{c}$, and the cost of the three swabs strategy grows very rapidly towards 100, the threshold value above which individual testing is less costly. Considering that the three-swabs strategy carries also higher organizational costs, the conclusion is that it is not worth implementing unless the relative device cost is very small as compared to the processing cost.

5 Conclusion

It is well known that the two-samples, group testing, strategy can significantly reduce the number of test required to perfectly screen a population, therefore increasing the labs capacity to process tests for a fixed amount of assigned resources. In this paper I showed that a lab that adopts this strategy can safely increase its capacity and be sure to process a significant number of additional test responding within one day even in worse case scenarios with a much bigger fraction of positives than expected and/or in case of many positive individuals scattered among groups.

In the Covid-19 case, the scarcity of reagents and of trained professionals is among the first reasons why an insufficient fraction of the population has been screened, with the consequence of a much faster virus diffusion. Moreover, the time spent waiting to be tested or to receive the test result puts a significant burden both on the quarantined individuals that cannot work and on the society in general.

The two-swabs strategy generates a small additional discomfort for the tested individuals, but the samples can be actually taken contemporaneously, perhaps with smaller swabs. Clearly communicating the reasons why two swabs are used will also significantly increase cooperation from the tested subjects. There could also be congestion effects, for instance longer lines in front of the lab that might discourage individuals from taking a test (assuming that they are not required to do so), but such effects are likely to be minor.

The two-swabs strategy will not work in case of tests to symptomatic individuals, say at the hospital or in the emergency room, because there is a high fraction of expected positives. However it will work very well for mandatory screening after contact tracing: when testing all recent contacts of an infected individual, given the relatively small basic reproduction number of the Covid-19 virus, there will not be a high number of expected positives. In general, the strategy to make the two-swabs strategy work is to test a wide number of people so to have a small expected fraction of positives. It's a sort of a paradox: the bigger the number of tested subjects, the lower the expected number of positive and the lower the final cost of the tests.

An additional benefit of the two-swabs strategy is that it will also reduce the number of false positives, because each positive individual is tested twice. Notice also that it is perfectly possible to have a positive test for the group and a negative for the individuals. This can happen if there is not enough virus to be detected in individual samples but that becomes detectable if more samples are bunched. The correct behavior in such cases is the following: if infected with very low viral charges are contagious, then all of the group members must be quarantine; if they are not, then the result is a negative for the group.

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Table 1: **Group Size, Number of Tests and Capacity Multiplier**

Fraction of Positives (π)	**Group Size** (n)	**Test Number** (T)	**Capacity Multiplier** (LCM)
0.5	15	12.461	7.189
1.0	11	19.557	5.113
1.5	9	23.828	4.196
2.0	8	27.423	3.646
2.5	7	30.527	3.275
3.0	6	33.369	2.996
3.5	6	35.913	2.784
4.0	6	38.391	2.604
4.5	5	40.564	2.465
5.0	5	42.621	2.346
5.5	5	44.637	2.240
6.0	5	46.609	2.145
6.5	5	48.541	2.060
7.0	4	50.195	1.992
7.5	4	51.791	1.930
8.0	4	53.361	1.874
8.5	4	54.905	1.821
9.0	4	56.425	1.772
9.5	4	57.919	1.726
10	4	59.391	1.683

Notes: The expected number of positives π is the probability of finding a positive in the test. The group size n is the one that minimizes the expected number of test in the two-swabs strategy. Test Number T is the expected number of tests required to perfectly screen $n = 100$ individuals The expected lab capacity multiplier LCM is the ratio between the number of tested individuals n and the expected number of tests in the two-swabs example for the optimal choice of the group size.

Table 2: **Expected Cost**

	$\pi = 1.5\%$	$\pi = 3\%$
Device Cost ($\bar{c}$)	Expected Cost (S)	Expected Cost (S)
0.01	25.57	35.02
0.025	28.13	37.44
0.05	32.22	41.31
0.10	39.84	48.52
0.15	46.81	55.11
0.20	53.19	61.14
0.25	59.06	66.69
0.30	64.48	71.82
0.35	69.51	76.57
0.40	74.16	80.98
0.45	78.51	85.08
0.50	82.55	88.91

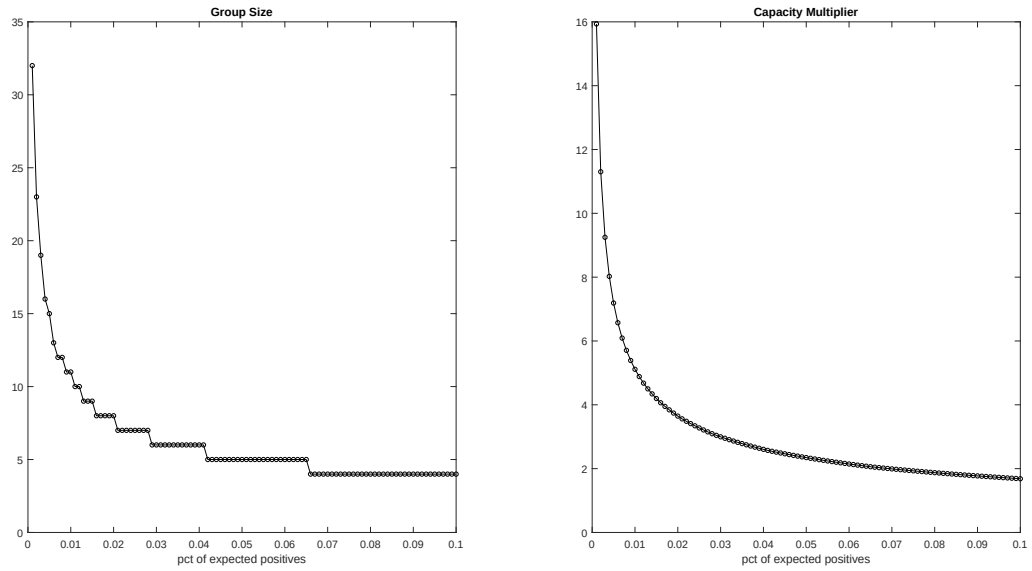
Notes: $\bar{c}$ is the ratio of the device cost c to the test processing cost C S is the expected cost of the two-swabs strategy as a fraction of the cost of the individual tests. π is the probability of finding a positive in the test.

Table 3: **Simulation Results**

	$\pi = 0.015$ $g = 9$				$\pi = 0.02$ $g = 8$			
	Median		Worse		Median		Worse	
$\hat{\pi}$	Multiplier (LCM)	Cost (S)	Multiplier (LCM)	Cost (S)	Multiplier (LCM)	Cost (S)	Multiplier (LCM)	Cost (S)
0.5	6.410	32.364	4.219	39.727	6.061	33.182	4.367	39.000
1.0	4.975	36.455	3.236	46.273	5.076	36.091	3.413	44.818
1.5	4.219	39.727	2.755	51.182	4.219	39.727	2.933	49.182
2.0	3.663	43.000	2.506	54.455	3.610	43.364	2.571	53.545
2.5	3.236	46.273	2.208	59.364	3.236	46.273	2.132	60.818
3.0	2.825	50.364	1.972	64.273	2.933	49.182	2.028	63.000
3.5	2.625	52.818	1.783	69.182	2.681	52.091	1.876	66.636
4.0	2.398	56.091	1.701	71.636	2.469	55.000	1.745	70.273
4.5	2.208	59.364	1.626	74.091	2.288	57.909	1.745	70.273
5.0	2.083	61.818	1.580	75.727	2.169	60.091	1.590	75.364

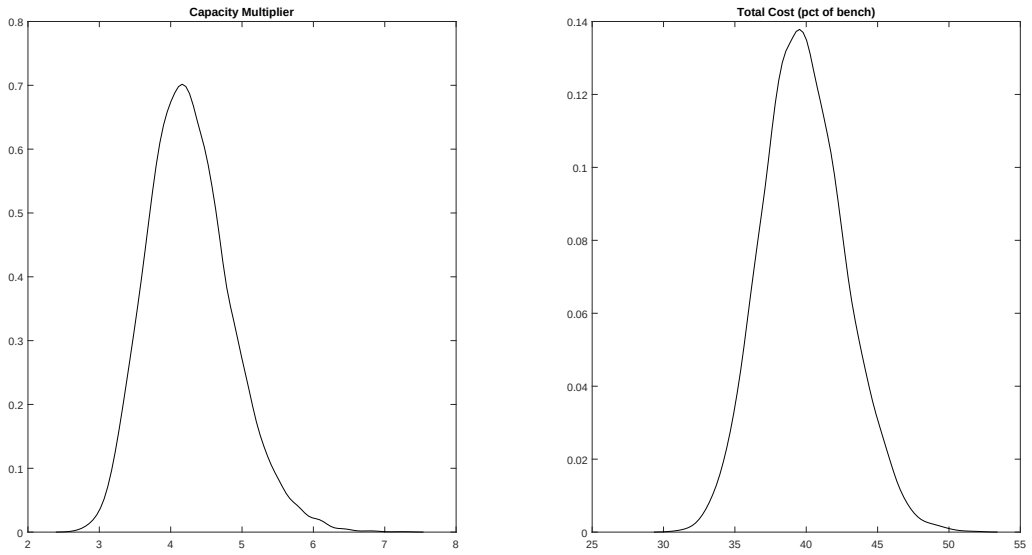
Notes: π is the expected number of positives in the population. $\hat{\pi}$ is the actual number of positives. g is the optimal group size based on the expected number of positives LCM is median lab capacity multiplier. S is the median cost of the two-swabs strategy as a fraction of the cost of the individual tests. 5000 simulation runs. Median refers to the median value of LCM and S over all simulation runs. Worse refers to the smaller value of LCM and the biggest value of W over all simulation runs (no extremes discarded).

Figure 1: **Output Group Size and Lab Capacity Multiplier**



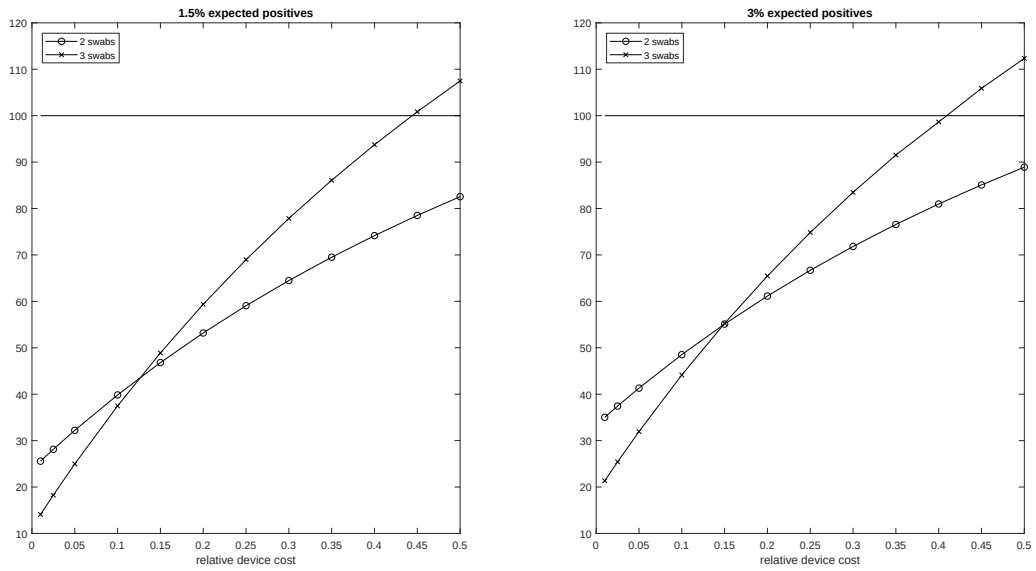
Notes: Left Panel: optimal group size g as a function of the expected number of positives π. Right Panel: Expected multiplier of the laboratory capacity LCM as a function of the expected number of positives π.

Figure 2: **Simulation Results**



Notes: Empirical distribution of the results of the two-swabs strategy over 5000 simulation. Left panel: multiplier of the laboratory capacity LCM. Right panel: Total cost as a ratio of the cost of the individual tests. Assumptions: $\pi = 1.5\%$, $g = 9$ and $\bar{c} = 0.1$.

Figure 3: **Total Cost, Three Swabs versus Two Swabs**



Notes: Total cost of the Two-swabs and Three-swabs strategies, expressed in terms of the cost of individual testing, as a function of the ratio $\bar{c}$ between the device cost c and the processing cost C. Left panel: 1.5% expected fraction of positives in the population (π). Right panel: 3% expected fraction of positives in the population (π).