Did people's behavior after receiving negative COVID-19 tests contribute to the spread?

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ABSTRACT

Background Testing on demand for coronavirus disease (COVID-19) is hypothesized to increase spread of the virus as some persons who test negative falsely assume that they can engage in activities that increase spread.

Methods Daily new COVID-19 hospitalization counts through 2020 from 25 countries that reported testing and hospitalizations were studied by regression of logarithms of new hospitalizations 14 days out against log(new hospitalizations on a given day), log(negative tests), log(positivity rate) and days since the first hospitalizations were reported. The regression coefficients were examined separately for periods in countries that were following three different testing policies.

Results Corrected for the other factors, negative test numbers when tested on demand and tested if symptomatic only are associated with an increase in hospitalizations 14 days after the tests. When only the symptomatic and more vulnerable are tested, negative tests are associated with fewer hospitalizations 2 weeks out.

Conclusions A policy of testing only vulnerable populations, whether symptomatic or not, appears to avoid spreading the virus as a result of testing policy. False confidence of reduced risk among those who test negative may have contributed to the spread in countries that allowed testing on demand or testing only those who claimed to have symptoms.

Keywords corona virus, infectious disease testing, social behavior, public policy

Introduction

Spread of infectious diseases that are transmitted person-to-person depends on the behavior of people in response to warnings and other public policies as well as the ease of transmission among people.[1,2] The ease of transmission of the coronavirus known as coronavirus disease (COVID-19) by aerosols in breath and the ubiquity of human social contacts and travel quickly resulted in a pandemic in early 2020 and resurged from time to time in many countries throughout the year. Public policy responses to the COVID-19 pandemic varied among countries and, in some cases, among provinces, states and cities within countries. As biological tests of infection of individuals by the virus became available, countries that used tests to identify cases adopted one of three testing policies: (i) test persons who present with symptoms, (ii) test persons with symptoms plus populations vulnerable to more severe outcomes such as people in nursing homes, the elderly generally, and persons with pre-existent conditions known to exacerbate severity of the disease. (iii) Test on demand including free testing in some countries.[3] The justification for the latter policy was to identify asymptomatic individuals who could nevertheless spread the virus to others as well as adjust other policies such as school, business and other closings based on the proportion positive of those tested. Tracing the contacts of those who tested positive and urging or requiring all who tested positive to quarantine themselves for 14 days would theoretically reduce the spread of the virus. Some countries changed testing policies and most changed elements of their preventive policies from time to time.

On-demand testing does not necessarily indicate the true positivity rate in a population because the people who self-select to be tested are not necessarily representative of the population. Furthermore, if enough people who receive a negative test behave in such a way as to increase their risk of exposure to the virus, the test-on-demand policy could result in increased spread of the virus. This hypothesis came to mind as news reports indicated long lines of people waiting to be

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tested prior to the Thanksgiving holiday in the US, a holiday traditionally marked by huge increases in travel to large family gatherings. Although public health officials issued repeated warnings that a negative test did not mean that one could not get the virus after the test and spread it to others, it appeared that a large number of people were ignoring the warnings and planning to travel if they received a negative test.

The purpose of this paper is to report differences in spread of COVID-19, as indicated by daily new hospitalizations during times when countries were testing only the symptomatic, the symptomatic plus the more vulnerable or allowing testing on demand. Hospitalizations are of particular interest because the diagnoses are likely more accurate than that for all cases and the number of hospital beds, health care personnel and equipment such as personal protection and ventilators available were less than needed in numerous cities at various point in time during 2020.

Materials and methods

Seven-day moving averages of daily numbers of tests, positivity rates and numbers of new hospitalizations for COVID-19 among countries where the data were available as of 31 December 2020 were downloaded from ourworldindata.org (https://ourworldindata.org/coronavirus-testing). Hasell *et al.*[4] provide a description of the database and derived variables as of 31 August 2020. The testing policy on a given day in each country was also downloaded from ourworldindata.org and was matched by country and date to the file containing tests and cases. Data on the same variables among US states were obtained from the COVID Tracking Project, Data Download | The COVID Tracking Project. Since symptoms in the infected may occur as much as 2 weeks after exposure, a least squares regression model was used to predict cases 2 weeks after a given day that a specified number of negative tests, hospitalizations and positivity occurred. The form of the model is:

$$\begin{aligned} Log\left(hospitalizations_{t+14}\right) = a &+ b_1 \log\left(hospitalizations_t\right) \\ &+ b_2 \log\left(negative\ tests_t\right) \\ &+ b_3 \log\left(positivity_t\right) + b_3(t) \end{aligned}$$

where t = time since first hospitalizations.

The number of negative tests on a given day was obtained by multiplying the positivity rate times the number of new tests on a given day and subtracting the result from the total number of tests. Taking the logarithm of the hospitalizations, negative tests and positivity reduced skew in the distributions. Controlling for cases at time t adjusts for the stage of the pandemic at a given time in a given country. If negative tests result in increased behavior that exposes the individual to risk of infection, then b_2 will be positive, indicative of an increase in cases 2 weeks out in relation to negative tests. The regression coefficients were estimated separately for each of the testing policies in countries other than the US The availability of US data by state provided the opportunity for replication of the results in a country where testing on demand was allowed and even encouraged in some states.

Results

Table 1 shows the regression coefficients and 95% confidence intervals for each of the policy groups in 24 countries and 47 US states that reported data on all the variables. Negative tests are associated with increases in COVID-19 hospitalizations during periods of test on demand and when those with symptoms only were tested. There were fewer hospitalizations predicted by negative tests during periods when only the symptomatic and vulnerable groups were tested. Higher positivity was associated with increased hospitalizations no matter what the policy, less so in the US than the other countries.

Since correlations among predictor variables can distort regression coefficients, the correlations presented in Table 2 were examined. A potentially distorting correlation was found between negative tests and hospitalizations in countries other than the US that had periods of testing on demand and testing symptoms only. None of the variables increased or decreased in parallel with time, a problem that can lead to false inferences in time series analyses.

Discussion

Main findings

These results are consistent with the hypothesis that people who receive negative COVID-19 tests behave in ways to increase spread of the virus. The warnings of public health officials that such behavior is unwarranted were apparently ignored by many people. The inverse correlation of negative tests to hospitalizations when testing is limited to vulnerable groups suggests that contact tracing of people in vulnerable groups and quarantine of those who tested positive is likely to have reduced the spread among the most vulnerable to the consequences of infection.

What is known?

These important datasets are missing a key piece of information: the number of tests in each policy group that were the result of tracing contacts of persons who tested positive. A few countries implemented contact tracing and enforcement of quarantines effectively for periods of time but most did not.[5] In the US with an on-demand testing policy, tracing

Table 1 New COVID-19 hospitalizations in 14 days predicted by number of new hospitalizations, negative tests, positivity on a given day and trend in time among 25 countries and 47 US states

	US states test on demand	*95% CI*	*Others test on demand*	*95% CI*	*Test symptomatic only*	*95% CI*	*Test symptomatic plus key groups*	*95% CI*
Log(hospitalizations)	0.832	0.818, 0.845	0.653	0.623, 0.683	0.760	0.738, 0.782	0.786	0.744, 0.828
Log(negative tests)	0.090	0.088, 0.092	0.250	0.217, 0.283	0.214	0.187, 0.241	−0.190	−0.089, −0.051
Log(positivity)	0.066	0.062, 0.086	0.460	0.427, 0.493	0.381	0.356, 0.406	0.400	0.358, o.442
Time	0.0006	0.0004, 0.0008	0.000	0.000, 0.000	.0004	0.0000, 0.0008	0.002	0.001, 0.003
Intercept	−.084		1.477		0.948		3.984	
N days	7593		1498		2170		912	
R-Square	0.84		0.94		0.98		0.88	

Table 2 Squared correlation coefficients among predictor variables

US on demand	*Log(negative tests)*	*Log(positivity)*	*Time*
Log(hospitalizations)	0.38	0.07	0.03
Log(negative tests)		0.03	0.30
Log(positivity)			0.00
Others on demand			
Log(hospitalizations)	0.56	0.44	0.00
Log(negative tests)		0.10	0.08
Log(positivity)			0.04
Test symptomatic only			
Log(hospitalizations)	0.61	0.31	0.01
Log(negative tests)		0.05	0.03
Log(positivity)			0.06
Test symptomatic plus vulnerable			
Log(hospitalizations)	0.38	0.35	0.00
Log(negative tests)		0.01	0.12
Log(positivity)			0.03

varied among the states and in many instances the number of cases overwhelmed tracer personnel to the point that tracing effectiveness was compromised. Many people, when traced, refused to be tested and some of those who tested positive refused to self-quarantine.[6] The limited supply of testing materials reduced the numbers tested in some areas. Nursing organizations complained that health care employers were not testing their members whereas professional and college sports teams were tested frequently. [7]

Without effective tracing and quarantine, the only benefit of testing is the positivity rate which can serve as a guide to preventive policies and preparation for surges in hospital patients. These were used in some US states to make decisions regarding closing schools, what businesses could remain open and the numbers of customers allowed at a time. Given the huge surge in hospitalizations in the fall of 2020,[8] these policies had limited effect either because the positivity rates are inaccurate due to nonrepresentative samples or too much delay occurred between the increase in positivity and implementation of policy changes.

Expensive and unrepresentative mass testing is not necessary to detect the spread of COVID-19 in a community. The spread of the virus is mainly in urbanized areas and is predictable based on local social, economic and demographic variables.[9] Tests of virus concentrations in community waste water have been shown to indicate the spread in the short term.[10,11]

What this study adds?

Other things being equal, unlimited COVID-19 testing likely contributed to the spread of the COVID-19 virus during periods when such testing was allowed or encouraged.

Limitations

Although the statistical results in this study are based on correlations that are not necessarily indicative of causation and are not based on observed behavior, the inference that they reflect behavior is plausible.

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Conflict of interest

The author has no financial or other interests that would be influenced by publication of this paper.

Data availability

Links to the data used in this study are provided in the methods section.

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