Title: Outdoor transmission of COVID-19: Analysis of windspeed

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Abstract

Background
To examine whether outdoor exposures may contribute to the COVID-19 epidemic, we hypothesized that slower outdoor windspeed is associated with increased risk of transmission when individuals socialize outside.

Methods
Daily COVID-19 incidence reported between 3/16/2020-12/31/2020 was the outcome. Average windspeed and maximal daily temperature were derived from the National Oceanic and Atmospheric Administration. Negative binomial regression was used to model incidence, adjusting for susceptible population size.

Results
Cases were very high in the initial wave but diminished quickly once lockdown procedures were enacted. Unadjusted and multivariable-adjusted analyses revealed that warmer days with windspeed <5.5 MPH had increased COVID-19 incidence (aIRR=1.50, 95% C.I.=[1.25-1.81], P<0.001) as compared to days with average windspeed ≥5.5 MPH.

Conclusion
This study suggests that outdoor transmission of COVID-19 may occur by noting that the risk of transmission of COVID-19 in the summer was highest on days when wind was reduced.
Background

The novel coronavirus SARS-CoV-2, which causes a potentially deadly disease called COVID-19 began spreading in China (1), and Italy (2) before arriving in the U.S. COVID-19 first hit in the U.S. in regions, such as NY and California, where global travelers often arrive into the U.S. (3). [COUNTY] experienced its first wave of infections early in March, when the pandemic had just arrived, causing a high degree of transmission and large numbers of COVID-related deaths.

COVID-19 transmits via aerosolized viral particles that begin shedding before symptoms are evident (4), making it difficult to trace patterns or locations where exposures are occurring. As a result, approximately half of those diagnosed with COVID-19 report not knowing where they may have become infected (5). The most likely explanation for this lack of known exposures is that COVID-19 transmits in spaces that are thought to be safe. A handful of studies have made some headway in identifying such situations. For example, one study found that COVID-19 could transmit through the air over relatively long distances (6) and another highlighted the impact of air conditioning vents (7). A third study found that a cluster of 17 cases could be traced to indirect transmission in shared spaces at a shopping mall in Wenzhou, China (8). Still other studies have revealed that individuals in a constricted space could spread COVID-19 via inhaled transmission over potentially large distances by following air flow within a restaurant (7) and within the Diamond Princess cruise ship (6).

A recent review concluded that transmission within constricted indoor spaces is critically important, but outdoor exposures may be possible yet little is known about their dynamics or specific pathways (9). There are reports of sporadic outbreaks in outdoor environments, including at a construction site in Singapore (10, 11), jogging (10), or during conversation (12).
Because of much lower risk outdoors, close outdoor contacts are often discussed as though they are risk-free and exposure-mitigating strategies have focused on promoting the use of exterior spaces when conducting social activities in efforts to mitigate risk of exposure. If exposure occurs outside, it is likely to be hampered by the same factors as are commonly seen in studies of indoor transmission including the air turnover rate. In the current study, we hypothesized that lower exterior wind speed would be associated with increased risk of transmission during warmer days, when individuals were most likely to be socializing outside.

**Method**

To examine the potential for exterior exposure risk, we modeled incidence of cases reported to the [COUNTY] Department of Health from March 16th, when data first began being recorded reliably using an electronic interface, until December 31st, 2020, at which time the COUNTY was enduring a second wave. Data were shared with [INSTITUTION BLINDED] for the purposes of supporting the COVID-19 modeling efforts at the local level.

**Ethics**

The analysis of publicly available deidentified case counts retrieved from the internet are considered to be not human subjects research and are exempt from ethics review.

**Measures**

The main outcome was the number of daily confirmed incident cases as reported by the [COUNTY] Department of Health. We limited analysis to dates following March 16th, 2020 with the opening of multiple drive-through testing sites throughout the area and when case-reporting
routines were established. Population at risk estimates come from population estimates for the county derived from the U.S. census; susceptible population counts were updated for daily death counts, and for the reported number of COVID-19-related disease counts.

Since daily case counts exhibit temporal dependence that is primarily determined by the underlying community force of infection, which cannot be measured directly, in a secondary analysis, we use an alternative outcome measure of a relative change in daily case counts compared to an 8-day forward/backward moving average defined as:

$$\frac{\text{cases}(t) - \frac{1}{8} \sum_{k=t-4}^{t+4} \text{cases}(k)}{\frac{1}{8} \sum_{k=t-4}^{t+4} \text{cases}(k)} \quad \forall \ k \neq t$$

The 8-day forward/backward moving average serves as a proxy measure of underlying force of infection allowing to partially capture the variability in absolute case counts that is due to “natural” transmission patterns rather than external shocks such as wind speed. It is important to note that, on average, this measure would be zero when case counts remain relatively constant over time, however during the periods of exponential rise and decay of an epidemic, this measure would on average be negative, and it would be positive around the peak of an epidemic curve. It is therefore important to take these distinct behaviors into account.

*Maximal daily temperature* as well as *average windspeed* were derived from the *National Oceanic and Atmospheric Administration* (NOAA) data portal (w2.weather.gov); data were recorded at a central location at the [LOCATION BLINDED]. Total snowfall and rainfall were also recorded in inches. While warmer temperatures are likely to be protective, as warm days allow individuals to socialize outside, where exposure appears to be markedly lower, increased windspeed may have diverging effects depending on temperature. In the summer, higher
windspeed increases air flow and may reduce risk \textit{versus} in the winter when it may work to push social contacts that were occurring outside to shelter in indoor spaces. When exterior temperatures are warm enough to allow for outdoor social contacts to occur comfortably, we anticipated that increased windspeed would reduce overall outdoor risk. In contrast, on days where exterior temperatures were cooler, increased windspeed might cause individuals to retreat indoors for social occasions.

\textit{Covariates}

We adjusted for number of days since lockdown (March 16\textsuperscript{th}, 2020) and days since reopening began in [COUNTY]. To account for differences in daily reporting patterns, we incorporated a categorial variable indicating the day of the week that cases were reported. Noting that there has been significant spread in [COUNTY] following holidays, we incorporated an indicator of holidays that also incorporated the most significant weekend nearby. We also included covariates measuring rainfall and snowfall as these weather conditions are hypothesized to correlate with windspeed as well as social activities outdoors. In the primary analysis, we also adjust for the 8-day forward/backward moving average daily case count.

\textit{Statistical Modeling}

Descriptive characteristics include time-related trends in maximal temperature, daily windspeed, and daily case counts. Trends in maximal temperature and in average windspeed were provided alongside smoothed polynomial best-fitting trend lines.

In the main analysis, incidence of COVID-19 positive caseload is reported as counts per day and, therefore, multivariable-adjusted modeling relied on negative binomial regression (13). Negative
binomial regression was chosen over alternatives including Poisson because we were concerned about the potential for over-dispersion in the outcome (14) since the infectious disease case load is highly variable, and because COVID-19 appears to spread commonly through superspreading clusters (15). A nine-day lag between exposure and case registration was assumed, consistent with epidemiological estimates of the incubation period for COVID-19 (16, 17) coupled with a two-day testing and one-day reporting lag period for available estimates online. Unadjusted and multivariable-adjusted incidence rate ratios (IRR) and 95% confidence intervals (95% C.I.) were reported. The interval between infection and disease ascertainment is not well known and varies geographically because it depends substantially on local testing availability and reporting systems – it can be reduced in places where testing is easy to find and lengthened in places where testing is difficult or requires hospitalization. As such, we conduct a sensitivity analysis considering the values of time intervals between exposure and case reporting between 5-15 days. For our lagging period, we allowed five days was chosen because our experience suggests that it takes two days to report results of testing to the DOH and an additional day to report those results online. Fifteen days was selected as a ceiling for index case analysis to reduce the risk of sequential effects of prior case/exposure cycles; however, sensitivity analyses reported results from 5-21 days to clarify the impact of those choices. The log-likelihood estimate was reported to compare model fit for different lags.

We analyzed the secondary outcome – a relative measure of daily case counts – using linear regression with the same set of covariates as the primary outcome measure and exploring the results for a range of reporting lags.
Since we hypothesized the effect heterogeneity of windspeed on transmission depending on the temperature, cutoffs for “warm” days and for days when windspeed was sufficiently fast were determined by comparing Akaike’s information criterion (AIC) across multiple models using different details as modeled parameters. We compared AIC between models to determine that >60°F [15°C] was an optimal cutoff for temperature. Because cutoffs may be useful when adjudicating risk at the local level, we similarly used AIC and compared model fit using multivariable adjusted models to identify optimal cutoffs for windspeed and ultimately identified low windspeed as days where windspeed was <5.5 MPH as the optimal cutoff for these models.

Since the relative measure of daily case counts only partially adjusts for the community force of infection and underlying “natural” epidemic dynamics, we also conducted additional stratified sensitivity analyses cut into time periods when case counts were relatively flat (06/07/2020-11/03/2020) and when epidemic was exponentially increasing (03/16/2020-04/10/2020 and 11/04/2020-12/31/2020) or decaying (04/11/2020-06/06/2020). We use two criteria: daily temperature (warm/cool) and epidemic dynamics pattern (flat versus rising or decaying) to determine subsets for stratified analyses. Analyses were completed using Stata 16/MP [StataCorp].

Ethics

Data used in this study are secondary analyses of de-identified case counts reported on a publicly available website and therefore this was not human subject’s research.

Results
We begin by showing the number of daily cases over the entire observational window (Figure 1). Cases were very high in the initial wave but diminished quickly once lockdown procedures were enacted.

**Figure 1.** Trends in daily COVID-19 cases identified in [COUNTY] from March 16\textsuperscript{th} – December 31\textsuperscript{st}, 2020

The average temperature was 67.6 ± 14.4 °F, the average daily windspeed was 8.7 ± 3.6 MPH. Trends in daily temperature and windspeed are depicted throughout the analytic period (Figure 2). Most days between May 1\textsuperscript{st}, 2020 and October 24\textsuperscript{th}, 2020 were characterized by temperatures exceeding 60°F (blue dashed lines; solid trend line). Windspeed diminished slowly over time, and then began to increase again in December 2020.
**Figure 2.** Trends in maximal daily temperatures, expressed in °F, and mean daily windspeed expressed in miles per hour in [COUNTY] from March 16th – December 31st, 2020

Further interrogating the functional shape of the relationship between the windspeed and incidence (Figure 3), we found that during “warm” time period higher windspeed was associated with diminishing degree of protection. Using the logarithmic transformation to capture this tapering in a multivariable-adjusted model, we found that while an increase in windspeed from 1 to 2 MPH is associated with a 4.2% reduction in caseload as compared to days when the air was still, a similar increase from 10 to 11 MPH was only associated with a 0.08% decrease in caseload on the “warm” days.

**Figure 3.** Average windspeed versus number of incident cases of COVID-19 in [COUNTY] from March 16th – December 31st, 2020
Note: The natural log function was selected because it performed better (AIC = 4055.4) than alternative specifications including linear (AIC = 4105.3), inverse (AIC = 4298.5), and quadratic (AIC = 4057.3). Unadjusted and multivariable-adjusted models are shown in Table 2. Note that the Incidence was lagged from windspeeds by nine days.

Unadjusted analyses revealed statistically significant associations between higher COVID-19 incidence and lower windspeed in warmer weather (Table 1). Multivariable-adjusted analyses similarly revealed that results remained statistically significant upon adjusting for confounders.

Table 1. Incidence rate ratios derived from negative binomial regression showing both unadjusted and multivariable adjusted analyses from March 16th – December 31st, 2020

| Variable                          | Unadjusted IRR [95% C.I.] | Multivariable Adjusted aIRR [95% C.I.] |
|----------------------------------|---------------------------|----------------------------------------|
| Maximal Temperatures >60°F       |                           |                                        |
| Maximal Temperature ≤60°F        |                           |                                        |
| Mean on days >60°F               |                           |                                        |
| Mean on days with ≤60°F          |                           |                                        |
| 95% C.I.                         |                           |                                        |
As noted in the Methods section, cutoffs were determined to be $>60^\circ F$ \([21^\circ C]\) in temperature, and $<5.5$ MPH in windspeed. Using these cutoffs, in Table 2 we examined the risk associated with lower windspeed ($<5.5$ MPH) on warmer days ($>60^\circ F$). Analyses revealed that on warmer days, having windspeed $<5.5$ MPH was associated with a 50% increase in incidence in multivariable adjusted models.

Table 2. Incidence rate ratios derived from negative binomial regression showing both unadjusted and multivariable adjusted analyses comparing days where windspeed $<5.5$ MPH to days with $>5.5$ MPH windspeeds (reference) from March 16th – December 31st, 2020.

| Variable                                      | Unadjusted          | Multivariable Adjusted |
|-----------------------------------------------|---------------------|------------------------|
| Windspeed ($<5.5$ MPH when temperature $>60^\circ F$) | 6.06 [4.78-7.69]    | 1.50 [1.25-1.81]       |
| Maximal Exterior Temperature, °F              | 1.00 [0.99-1.01]     | 1.00 [0.93-1.34]       |
| Days since Lockdown                           | 0.95 [0.94-0.97]     | 0.95 [0.94-0.97]       |
| Days since Reopening                          | 1.06 [1.04-1.07]     | 1.06 [1.04-1.07]       |
| Holiday Adjustment                            | 1.11 [0.93-1.34]     | 1.11 [0.93-1.34]       |
| Snowfall, inches                              | 0.96 [0.84-1.10]     | 0.96 [0.84-1.10]       |
| Rainfall, inches                              | 1.02 [0.87-1.20]     | 1.02 [0.87-1.20]       |
| Eight-day forward/backward moving average     | 1.22 [1.20-1.24]     | 1.22 [1.20-1.24]       |

Note: IRR: Incidence rate ratio; 95% C.I.: 95% confidence interval. All models additionally adjust for day of the week in which cases were reported and for the size of the county population adjusted for reductions due to individuals who had died or became immune due to COVID-19 during the period of observation. Alpha is a measure of dispersion. P-values derived from Student’s T test.
| Variable                                | Estimate   | 95% CI     | P-value  |
|-----------------------------------------|------------|------------|----------|
| Windspeed <5.5 MPH when temperature ≤60°F | 2.11       | [1.54-2.88]| < 0.001 |
| Exterior Temperature, °F                | 1.12       | [0.93-1.35]| 0.229    |
| Days since Lockdown                     | 0.96       | [0.94-0.97]| < 0.001 |
| Days since Reopening                    | 1.05       | [1.03-1.07]| < 0.001 |
| Holiday Adjustment                      | 1.15       | [0.96-1.38]| 0.125    |
| Snowfall, mm                            | 0.95       | [0.83-1.09]| 0.456    |
| Rainfall, mm                            | 1.00       | [0.85-1.17]| 0.988    |
| Eight-day forward/backward moving average | 1.22     | [1.2-1.25] | < 0.001 |
| α                                       | 0.78       | [0.67-0.9] | 0.19 [0.16-0.22] |

Note: *Warm days were defined as >60°F while slow windspeed was defined as <5.5 MPH. MPH: Miles Per Hour; °F: degrees Fahrenheit; IRR: incidence rate ratio; 95% C.I.: 95% confidence interval. All models adjust for day of the week in which cases were reported and for the size of the county population adjusted for reductions due to individuals who had died or become immune due to COVID-19 during the period of observation. Alpha is a measure of dispersion. P-values derived from Student’s T test.

Sensitivity Analysis

We examined the sensitivity of the results to analytic choices by first examining whether reliance on different outcomes made differences to the results. For the relative change in daily case counts compared to an 8-day forward/backward moving average, the results were substantively similar (B = -16.12 [-27.78, -4.45], P=0.007) on warmer days; in other words, as windspeed decreased by one MPH, incidence increased by 16.12% (Table S1). We also examined whether choices in the lag between exposure and case reporting changed our results. While the results shown theoretically represent the appropriate timing, we also examined variation in periods between exposure and case recording from 5-21 days. We found that while the nine-day reporting average was the best performing within our hypothesized observational window
(Figure S1), that the 16-day reporting lag was the best performing lag structure. Across all lags, a consistently association was identified linking slower windspeed days with lower follow-up case counts (Table S2). Finally, we stratified analysis dates into periods characterized by rising, falling, and stable exposures as defined by rapid sustained increases resulted in the same overall association (aIRR$_{5.5\text{MPH}} = 0.87$ [0.75-1.03]; aIRR$_{1.0\text{MPH}} = 0.88$ [0.75-1.05]) though insufficient observations to achieve statistical power (power = 0.65).

Discussion

COVID-19 is a pandemic that has caused an immense toll on the American population and has inflicted enormous economic damage. To date, relatively little remains clear about the exposure dynamics of the disease. Current evidence suggests that COVID-19 is airborne and is predominantly spread indoors. The present study examined variation in windspeed under the hypothesis that higher winds may disperse COVID-19 viral particles away from individuals who are socializing outdoors, thereby offering increased protection among individuals who may have been exposed to COVID-19 outdoors. We found that slow average windspeed (<5.5 MPH) was associated with increased incidence on days that were warm enough (>60°F [15°C]) to allow individuals to socialize outdoors (aIRR = 1.50 [1.25-1.81], P < 0.001). This study supports the view that outdoor transmission of COVID-19 may be occurring by noting that the risk of outdoor transmission of COVID-19 was highest on days where wind was reduced.

This study suggests that outdoor exposures may be a pathway of COVID-19 transmission. This aligns with a number of anecdotal reports from Departments of Health in [COUNTY] (CITE personal communication) and from the Centers for Disease Control and Prevention (18), who have noted that gatherings of increased risk include outdoor social gatherings such as “Backyard
barbecues” despite no scholarly evidence to support that conclusion. Indeed, backyard barbecues have been thought in [COUNTY] to be a main source of exposure despite being outdoors. One interpretation of this evidence was that individuals may be using shared indoor spaces, such as bathrooms, where viral particles may be concentrated. However, an alternative may be that airborne transmission in shared outdoor spaces is feasible on days when wind is insufficient to disperse viral particles, and the data presented here support this alternative hypothesis.

Limitations

Despite examining a large population (~1.5 million) where a large number of cases (96,057 between March-December 2020) were identified, this study is limited in examining the experience of a single U.S. county. While this analysis suggests that county residents had fewer cases arising from days where winds were greater, we cannot conclusively state that individuals were protected because of higher windspeed. Our results were strongly influenced by covariates as evidenced by the change in IRR observed in unadjusted versus adjusted models; it is always possible that key confounders were missing from our model. However, our sensitivity analysis examining percent change of new cases on a given day relative to the 8-day backward/forward average case count, attempted to address temporal changes in incidence patterns directly within the outcome variable, and our results were similar. Follow-up research is necessary to determine specifics about exposures including distances that COVID-19 viral particles can travel and reliably infect individuals as well as microclimate differences that may affect specific geographic differences that may moderate these results.

To obtain a measure of windspeed for this analysis, we relied on data from a central airport. While this provided highly consistent measures of windspeed for the island, it also provides
measures that may not be generalizable to microclimates that can occur in the lee of hills, fenced-in backyards, or forests. Notably, this choice may mean that cutoffs used here may not apply in other situations and more analysis is necessary if weather data are going to be relied upon to help understand caseload in other areas. We reported results from a 9-day exposure-test positive reporting lag structure; however, sensitivity analyses suggested that a 16-day lag structure may work better. The 16-day lag is outside of the expected lag period for cases in our area, but we felt that it might indicate that case dynamics could proceed from asymptomatic younger individuals to cause secondary cases in older individuals reported 16 days later. As such, future work should anticipate that different cutoffs will be necessary when windspeeds are measured in different places and in locations where wind is highly sensitive to local geography.

Implications

Throughout the U.S. epidemic, the role of outdoor shared spaces such as parks and beaches has been considered and ultimately beaches and parks remained open. This analysis does little to suggest that either should be closed, since the level of risk due to outdoor exposures should be weighed in relation to the much higher risk of exposure in shared interior spaces such as houses, restaurants, or public transport. Instead, this study suggests that individuals socializing outdoors are not entirely safe by virtue of being outdoors and should remain vigilant. In this case, outdoor use of increased physical distance between individuals, improved air circulation, and use of masks in outdoor environments may be useful.
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Table S1. Multivariable-adjusted regression coefficient, 95% confidence interval, and P-values examining association between windspeed (>5.5 MPH) on warm days and percentage increases in case numbers

| Variable                                      | Coef., 95% C.I., P  |
|-----------------------------------------------|---------------------|
| Windspeed <5.5 MPH when temperature >60°F     | -16.12 [-4.45, -27.78] P =0.007 |
| Windspeed <5.5 MPH when temperature ≤60°F     | -0.80 [-3.03, 1.43] P =0.479  |
| Exterior Temperature, °F                      | 0.06 [-1.09, 1.22] P =0.913 |
| Lockdown                                      | -0.56 [-2.73, 1.61] P =0.611 |
| Reopening                                      | 0.61 [-1.79, 3.02] P =0.615 |
| Holiday Adjustment                            | 8.87 [-16.41, 34.15] P =0.490 |
| Snowfall, mm                                  | 0.40 [-19.24, 20.05] P =0.968 |
| Rainfall, mm                                  | -0.85 [-22.25, 20.55] P =0.938 |
| Eight-day forward/backward moving average     | -2.26 [-4.80, 0.28] P =0.081 |
Table S2. Multivariable-adjusted incidence rate ratio (aIRR), 95% confidence interval, and P-values examining association between windspeed (>5.5 MPH) on warm days and increases in case numbers

| Lagged Days | aIRR  | 95% C.I.    | P     |
|------------|-------|-------------|-------|
| 5          | 0.867 | 0.791-0.950 | 0.002 |
| 6          | 0.883 | 0.806-0.968 | 0.008 |
| 7          | 0.944 | 0.861-1.034 | 0.214 |
| 8          | 0.889 | 0.813-0.973 | 0.011 |
| 9          | 0.830 | 0.759-0.908 | <0.001|
| 10         | 0.871 | 0.796-0.954 | 0.003 |
| 11         | 0.922 | 0.844-1.007 | 0.072 |
| 12         | 0.868 | 0.796-0.946 | 0.001 |
| 13         | 0.901 | 0.826-0.982 | 0.019 |
| 14         | 0.940 | 0.862-1.026 | 0.168 |
| 15         | 0.903 | 0.828-0.985 | 0.022 |
| 16         | 0.865 | 0.794-0.942 | 0.001 |
| 17         | 0.883 | 0.811-0.961 | 0.004 |
| 18         | 0.934 | 0.857-1.018 | 0.121 |
| 19         | 0.902 | 0.829-0.982 | 0.018 |
| 20         | 0.877 | 0.804-0.957 | 0.004 |
| 21         | 0.920 | 0.842-1.005 | 0.066 |
**Figure S1.** Gaussian-smoothed fit characteristics for the model presented in Table 1 relying on different lag structures examining possible lags of 4-14 days. Note that the best fitting date was shown using a red diamond.