**Lagged Association of Relative Humidity with Excess Death Rates during the Covid-19 Pandemic in the United States**

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**Abstract**

While studies have indicated an association between low relative humidity (RH) and the spread of covid-19, little is known either about the magnitude of the association in terms of death rates at the community level or about its value as a leading indicator of future death rates. This retrospective cross-sectional monthly time series (panel) study analyzed U.S. state excess death and RH data in combination with various controls from 5/2020 through 2/2022. The association of RH with excess death rates 2 months later was estimated. Monthly data on 50 states plus the DC yielded a total of 1122 data points. Unadjusted, a state had 39% odds (95% CI [29.9%, 47.9%]) of an excess death rate above 30% if RH was at least 10% below the state’s median RH 2 months prior and only 4% odds ( [1.3%, 10.55%]) if RH was at least 10% above. A negative binomial regression of excess death vs. RH 2 months prior estimated that a 10% increase in RH was associated with a 18.3% ([12.3%, 24.0%]) relative decrease in excess death after controlling for vaccination and boosted rates, social distancing, mask mandates, temperature, cumulative case rates, current-month covid death rates, time-invariant state characteristics and nationwide time trends. With covid death rates as the outcome instead of excess death percentage , a 10% RH increase was associated with a 18.1% ( [13.7%, 22.3%] ) decrease. Results suggest low RH could serve as an early warning signal indicating increased risk of future covid spread.

**Introduction**

Several studies have indicated that low relative humidity (RH) increases the spread of covid-19 and influenza. Median covid-19 virus half-life was estimated at more than 24 hours at 10 degrees Celsius and 40% RH but only approximately 90 minutes at 27 degrees Celsius and 65% RH1. When mice were exposed to low RH conditions, they were more susceptible to influenza2. Larger respiratory droplets evaporate faster and stay in the air longer in low RH environments3. A study of influenza mortality and absolute humidity (a quantity closely related to RH) found that absolute humidity explains roughly half the seasonal variations in influenza mortality in urban settings 4.

However, little attention has been given in the scientific literature to epidemiological estimates of the magnitude of the association between RH and covid death rates at the community level after controlling for confounders such as non-pharmaceutical interventions, vaccination rates and temperature. There also has not been much focus on the ability of RH to serve as a leading indicator which might help predict spikes in covid death rates in the near future.

**Methods**

This study was designed and conducted according to the Strengthening the Reporting of Observational Studies in Epidemiology ([STROBE](https://www.equator-network.org/reporting-guidelines/strobe/)) reporting guidelines5.

**Study Design**

The structure of the study is a monthly time series (panel6) dataset of all-cause excess death and covid death data, RH data and various controls for all 50 U.S. states plus the District of Columbia. For the sake of brevity, the term “state” in this paper is used informally to include both U.S. states and the District of Columbia.

The study employs a hypothesis that the association between death rates and the exposure (RH) is likely to be strongest when there is a 2 month lag between exposure and death rates, with the same logic applying to controls as well as exposure. Since the time between covid infection and death is typically between 2 and 8 weeks7,8, a 1 month lag may have a weaker association, given that conditions towards the end of a month are too recent to expect an association with death rates early in the following month. However, the choice to focus on a 2 month lag is not meant to imply associations with other time lags (0 months, 1 month, 3 months, etc) are irrelevant or expected to be 0. The 2 month lag is chosen in part for the sake of simplicity of modeling strategy and presentation, but more sophisticated approaches in which multiple lags (or weighted averages thereof) would be used are viable alternatives and possible directions for future research.

**Setting**

The dataset includes U.S. state monthly excess death and covid death rates from May 2020 through February 2022, corresponding to monthly RH data and other controls from March 2020 through December 2021, given the two-month lag strategy of the study. Deaths for March and April 2020 were excluded because some control data regarding social distancing behavior was not available for January and February 2020. January and February 2020 may also be regarded as outlier months for the United States pandemic, given that it is unclear how significant U.S. covid infection rates were in January 2020 and given that covid was allowed to spread in a mostly uncontrolled fashion in February 2020.

**Variables**

All-cause excess death percentage was the primary outcome studied, with per-population covid death rates as a secondary outcome. Excess death data accounts for deaths caused by covid which may not have been documented as such, as well as the reverse. RH 2 months prior is the exposure studied.

**Data Sources**

Weekly RH and temperature data was downloaded from the service WeatherAPI9. Data was downloaded for one latitude/longitude location per U.S. county. Population-weighted monthly U.S. state averages were then derived from the weekly county-level weather data and county population data. As a quality check for the WeatherAPI RH data and for comparison purposes, long-term monthly average RH averaged over many years for each state was also obtained, from the National Centers for Environmental Information (NCEI) 10.

All-cause excess death data 11, covid-19 case and death data12 and covid-19 vaccination data 13 were obtained from publicly accessible websites hosted by the CDC.

Mobility data was obtained from Google COVID-19 Community Mobility Reports 14. The mobility reports use data on visits and length of stay at various types of locations to report a percentage change in mobility relative to a prepandemic baseline in January and early February of 2020. This paper uses mobility changes for 4 location categories: Retail/Recreation, Grocery/Pharmacy, Transit Stations and Workplaces. Previous analyses of covid non-pharmaceutical interventions 15,16 have employed the Google mobility report data.

Social distancing policy data was obtained from the Oxford Covid-19 Government Response Tracker project17,18. The project provides a stringency index which combines policies such as restrictions on the size of gatherings, workplace closures, the cancellation of public events and others into a single real-valued number ranging from 0 to 100. An increase in the stringency index was associated with lower covid-19 deaths in a study across 186 countries18.

Mask mandate data was obtained from the COVID-19 US State Policy Database19.

All data with the exception of the weather data was downloaded on July 25, 2022. Data from WeatherAPI was downloaded between May 21 and May 23, 2022.

**Statistical Analysis**

Two types of analyses were conducted: an unadjusted association analysis and a more rigorous panel regression with numerous controls.

The first analysis is a simple, unadjusted descriptive statistic measuring the odds of a state experiencing an excess death rate of at least 30 percent depending on whether the state’s difference from its median RH value 2 months previously was unusually low (below minus 10 percent ) or unusually high (above 10 percent) . Percent RH deviations here and elsewhere in the study refer to RH units rather than proportional change, so e.g. a 10 percent increase means moving from 60 percent RH to 70 percent RH, not 66 percent.

While the second, regression-based analysis with controls is far more rigorous, this first analysis provides a simple statistic useful for communication purposes with a broader, less technical audience. A statement of an unadjusted association of RH itself with excess death rates would be vulnerable to the obvious objection that high-RH and low-RH U.S. states may differ along various other, potential confounding dimensions. However, an association of unusual local RH levels with later excess death rates, while still potentially confounded, is much less vulnerable to obvious and immediate objections of confounding. Excess death percentage in the data sample averaged 17.7 percent in the sample with a standard deviation of 15.6 percent, so the 30 percent threshold is chosen to correspond roughly to 1 standard deviation above the mean while rounding down for the sake of simplicity of communication. The standard deviation of monthly RH for a U.S. state in the sample has a mean of 7.4 percent, so 10 percent RH deviation is chosen for similar reasons.

The second analysis is a negative binomial regression of monthly excess death rates of each state vs. the state’s average RH and various controls 2 months earlier. Negative binomial regression is commonly used for count and rate dependent variables and makes more flexible distributional assumptions than Poisson regression20.

The controls used for the negative binomial regression were as follows. Average temperature was controlled for, given associations between temperature and covid spread found in previous studies. The absolute value of the difference between current temperature and 68 degrees Fahrenheit was another control, accounting for the potential relationship between temperature and spending time outdoors. Vaccination and boosted rates were controlled for. The Oxford stringency index measuring social distancing policy is included as a control. State mask mandates are controlled for, coded as binary 1/0, with mandates applying for only for a fraction of a month taking on that fraction as a value. Social distancing behavior, quantified from the Google Mobility reports as previously described, was included as a control. Cumulative per-population covid case rates were included in an attempt to account for the level of natural immunity in the population as well as the degree of previous local experience treating covid. These cumulative case rates were measured as of a month earlier than the other controls, i.e., 3 months prior to the month where excess death was being forecasted, since case rates 2 months prior are a potential mediator of the association between RH 2 months prior and later death rates. Per-population covid death rates 2 months prior are controlled for to account for other local behavior changes being induced voluntarily by the current local death impact of covid. This control also accounts for the possibility that covid death waves tend to rise and fall on a roughly 2-month cycle for reasons independent of exposure and controls. A two-way fixed effects method was employed in which a coefficient was also estimated for each state as well as for each of the 22 months in the dataset, as is common in panel regressions4,6. The state-specific coefficient is intended to account for approximately time-invariant traits of each state which might predispose the state to higher or lower death rates, such as population density and rates of preexisting health conditions. The month-specific coefficient is intended to account for broad, nationwide time-varying conditions such as the emergence of new covid therapies and new virus variants as well as calendar-dependent behavior patterns such as gathering for holidays.

Table 1 provides summary statistics for outcomes and controls.

R version 3.6.1 was used. Standard errors were clustered by state to account for serial correlation of a state’s residuals using the vcovCL function in the R package ‘sandwich’.

**Results**

Figure 1 shows a scatter plot of excess death percentage vs deviation from median RH (i.e. RH minus the state’s median RH) 2 months prior. While small-magnitude RH deviations in the plot exhibit little correlation with future excess deaths (perhaps due to the multitude of other factors beyond RH), high excess death is far more likely 2 months after RH values well below median than after RH well above median.

There were 109 instances of a state experiencing a month where RH was at least 10 percent below its median value. For 42 of 109 such pairs, excess death percentage exceeded 30 percent 2 months later, a rate of 38.5 percent [29.9, 47.9]. There were 80 instances where RH was at least 10 percent above its median value. In only 3 of those instances was excess death above 30 percent 2 months later, a rate of 3.8 percent [1.3,10.5]. The baseline rate of excess death percentage exceeding 30 percent among the 1122 data points in the study was 19.3 percent [17.1,21.8].

22 states were represented among the 43 instances with excess above 30% and RH at least 10% below median 2 months prior, including e.g. Virginia, Nebraska and Oregon, suggesting the observed pattern was geographically broad-based.

The pattern cannot be summarized merely as coinciding with the better-known pattern of covid death rates generally being higher in winter months, when air may tend to be drier in some areas. If the data is restricted to March through October, there remain 53 instances of RH at least 10 percent below median, with 19 instances (35.8 pct [24.3,49.3]) having excess above 30 percent 2 months later. There are 62 instances with RH at least 10 percent above median and only 1 (1.6 percent [0.1 , 8.6]) with excess above 30 percent 2 months later.

To evaluate the credibility of observational analyses, some papers21,22 have suggested specifying ‘negative controls’ or ‘falsification end points’, in which the same methodology used to measure the primary association being studied is also used to detect whether a different association which should not exist is detected by the methodology. For instance, a well-controlled study on the impact of vaccinations probably should not detect an association of vaccination with physical trauma rates. Given the rationale already outlined for studying a 2-month lag , a much lower-magnitude association (possibly insignificant) would be expected between the deviation from median RH in the same month as the excess death month. 24 out of 115 instances with RH at least 10 percent below median (20.9 percent, [14.4,29.2]) experienced at least 30 percent excess death in that same month. 94 instances had same-month RH at least 10 percent above median and 13 out of 94 (13.8 percent [8.3,22.2]) had excess death above 30 percent in that same month. Thus, the “negative control” of same-month RH associations is consistent with known lags between infection and death. A one-month lag exhibits the expected intermediate association. 34 of 114 instances with RH at least 10 percent below median had excess above 30 percent one month later (29.8 percent [22.2,38.8] ). 5 of 82 instances with RH at least 10 percent below median exceeded 30 percent excess one month later (6.1 percent [2.6,13.5]). Similar “negative control” analyses for the regressions are in the appendix.

RH deviations with a roughly 2 month lead time appear notable when examining the timing of the highest excess death spikes of some states as well as when comparing the winter of ’20-’21 to the winter of ’21-’22 in certain states. South Dakota’s 105% excess death rate in November 2020 was preceded by 43% RH in September 2020 , far lower than the RH range (between 58% and 78%) which occurred between March and August 2020. Hawaii did not have a month above 9% excess until 22% excess in August 2021, which was preceded by RH of 68% in June 2021, its lowest of the pandemic and 1.9 standard deviations below median. California’s 62% excess death in December 2020 and 81% in January 2021 was preceded by 34% and 35% RH in September 2020 and October 2020. Unlike the ’20-’21 winter, excess death in California never rose above 36% from November 2021 through February 2022, following a corresponding period from September 2021 to December 2021 during which RH was never below 40% and averaged 50%. In contrast to California, Virginia’s 40% excess death rate in January 2022 was higher than at any point during the winter of ’20-’21. Two months prior, in November 2021, RH in Virginia was 60%, its lowest of the pandemic by more than 5%, 2.8 standard deviations below the median Virginia RH and much higher than the 73.3% occurring in November 2020.

The regression yielded a coefficient of -0.020 [-0.013, -0.027] for RH, corresponding to an association of an 18.3% [12.3%, 24.0%] relative decrease in excess death percentage with a 10% increase in RH 2 months prior, after accounting for the controls previously described. With covid death rate as the outcome rather than excess death rate, the coefficient was -0.020 [-0.015, -0.025]. Using long-term average RH from the NCEI and excess as outcome gives a similar coefficient: -0.021 [-0.011, -0.032]. Restricting the data to above national median RH of 71.7% yields -0.021 [-0.004,-0.038] and restricting to below 71.7% RH yields -0.025 [-0.016,-0.035].

Tables e1 and e2 in the appendix show regression coefficients for RH as well as for controls. Table e1 shows coefficients in terms of the natural units as shown in Table 1. Table e2 shows coefficients when RH and all controls are standardized to have zero mean and variance 1. Care should be taken when interpreting tables e1 and e2 not to commit Table 2 fallacy errors23, particularly as concerns the Oxford stringency index, whose association is mediated by the Google mobility variable.

Regression results were robust to removal of any 2 states. Regressions with all 1275 possible combinations of pairs of states removed were calculated. Point estimates for the coefficient ranged from -0.018 to -0.023, with 95% lower CI bounds ranging from -0.011 to -0.016 and upper bounds ranging from -0.025 to -0.030.

Further robustness checks are presented in the appendix.

**Discussion**

The study has several limitations. The study is ecological in nature, using averages over U.S states and over months. As such, care should be taken to interpret results while keeping in mind the possibility of making ecological fallacy errors24. In particular, there is potential for ecological fallacy errors to be made in the time dimension. It is possible that the associations found arise from intermittent short-term fluctuations where RH is much lower than the monthly average rather than those times when RH was very near the monthly average. Another limitation is that data is confined to the United States and results may not apply to areas outside the country. Although the 2-month lag modeling strategy suffices to identify a notable association, more sophisticated modeling using multiple time lags or weighted averages thereof are needed to gain a fuller understanding of the time lag dynamics.

The study findings are largely consistent with the more experimental and mechanistic research cited in the introduction. Previous covid virus viability findings1 suggest a U-shaped RH dependence whereas evaporative effects3 suggest a more monotonic RH dependence. The regression results at above-median RH may indicate the importance of evaporative effects at higher RH. The findings may also lend additional support to proposals made to use indoor humidification as a mitigation strategy for reducing covid-19 transmission25 , while also taking care not to promote mold via excessive humidification.

All data and code used to produce the paper are available at a publicly accessible github26.

**Conclusions**

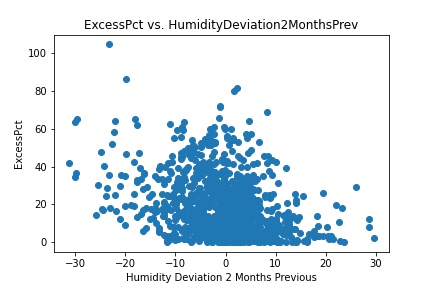
This observational study found that lower RH in the United States was associated with higher all-cause excess death rates and covid death rates 2 months later. Heightened promotion of mitigation efforts when unusually low local levels of RH occur may be worth considering. Studies assessing the efficacy of various interventions for combatting covid-19 deaths may also benefit from controlling for local levels of RH. The reasons for variation in covid death rates across U.S. states and their relationship with various mitigations efforts are also of interest to the general public. The role of RH in the covid pandemic may provide valuable context for public health messaging.

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**Figure 1 Title:**

“Excess death percentage vs. deviation from median relative humidity 2 months previously”.

**Figure 1 Legend**

Figure 1 plots the deviation from median relative humidity (defined as monthly average relative humidity minus the state’s median monthy average relative humidity) versus excess death percentage for the month occurring 2 months later. Low excess death is very rare 2 months after unusually low relative humidity, while high excess death is very rare 2 months after unusually high relative humidity.

**Appendix: Detailed Regression Results**

In this appendix, more detailed regression results and robustness checks are presented.

Table e1 presents regression results for the main regression result of the paper, i.e., excess death percentage vs. RH and all controls 2 months previously.

Some remarks about the mechanics of the negative binomial model may be helpful when interpreting the coefficients. Negative binomial regression models the log of the outcome as a linear combination of independent variables (i.e. exposure and controls), corresponding to a multiplicative model in terms of the outcome as a function of independent variables, where the multiplicative factor for a particular variable is an exponential of the coefficient times the variable. For instance, the -0.0203 for RH in Table e1 means that a 1% increase in RH (coded as 1 as indicated in Table 1 in the main paper, not 0.01) is associated with multiplier of exp(-0.0203) = 0.9799 modifying a baseline prediction. For a 10% RH increase, exp(-0.203)=0.9799^10=0.8165, yielding the 18.4% relative decrease in excess death percentage result in the main paper.

There is a very wide range of scales of natural units in the controls. To make the coefficients more easily comparable, Table e2 presents an equivalent regression where RH and all controls (but not the excess percentage outcome) are standardized to have zero mean and variance 1.

Caution is advised when drawing inferences from control coefficients, given that the set of appropriate controls for one exposure such as RH may not necessarily be the appropriate set of controls for another exposure1 . The coefficient on the stringency index has particular potential for misinterpretation, given that social distancing policy stringency is likely mediated by the actual behavior represented by the Google mobility data. A previous study of social distancing policy 2 takes the approach of regressing mobility vs. stringency index and controlling for the residual of that regression (rather than mobility itself) as well as for the stringency index. Following the same procedure here yields a coefficient of -0.019 [-0.004, -0.034] for the stringency index and -0.025 [-0.005, -0.045] for the mobility residual. The RH coefficient is virtually the same: -0.0203 [-0.013, -0.027]. As this residualizing technique is somewhat unusual and as the focus of the paper is RH rather than social distancing policy, this methodology is not presented in the main paper but it may be worth considering if the same dataset is used in the future for studies which focus on social distancing.

Regression results are robust to choice of controls. An unadjusted negative binomial regression of excess percentage vs. RH two months previously yields a fairly similar result: -0.016 [-0.010, - 0.021]. Although it would be highly inappropriate statistical methodology to search systematically over a large set of possible combinations of controls, even if one were to do so in search of a combination where the RH association is not significant, none would be found. All possible subsets of controls yield negative coefficients and negative 95% CI bounds, with -0.008 the smallest-magnitude estimate and -0.003 the smallest-magnitude 95% CI bound.

Dividing the data sample in half and using data only through March 2021 and excluding vaccination and boosted rates as controls, the estimated coefficient is -0.029 [-0.019, -0.038]. Using only data from April 2021 onwards, the estimated coefficient is -0.010 [-0.002, -0.018].

Using a 1 month or 0 month lag rather than a 2 month lag for RH (while holding other controls constant) yields an attenuated association as the lag decreases, similar to the negative control results presented in the main paper for the unadjusted association. The coefficient for a 1 month lag is -0.015 [-0.010, -0.020] and for a 0 month lag the coefficient is -0.010 [-0.004, -0.016]. Note that while the statistical significance of shorter lag associations could stem to some extent from actual impacts on death on a shorter time scale, they could also stem from correlation with RH at a 2 month lag. RH with a 2 month lag has a correlation of 0.75 with RH with a 0 month lag and 0.84 with a 1 month lag.

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| **Table e1: Regression Coefficients** | | |
| **Variable** | **Coefficient** | **P-value** |
| Relative Humidity 2 Months Previous | -0.0203 [-0.0131,  -0.0275] | 3.3e-8 |
| Stringency Index 2 Months Previous | -0.0065 [0.0052,  -0.0181] | 0.28 |
| Mask Mandates 2 Months Previous | -0.3466 [-0.1819,  -0.5114] | 3.7e-5 |
| Mobility Reduction 2 Months Previous | -0.0251 [-0.0047,  -0.0456] | 0.0160825 |
| Cumulative Cases Per 330M people 3 Months Previous | -7.34e-8 [-5.69e-8,  -9.00e-8] | < 2.2e-16 |
| Deviation from 68 Fahrenheit 2 Months Previous | -0.00372 [7.02e-3,  -1.45 e-2] | 0.4968128 |
| Covid Deaths Per 330 Million 2 Months Previous | -3.56 e-6 [-1.94e-6,  -5.18e-6] | 1.601e-05 |
| Fahrenheit Temperature 2 Months Previous | -0.030 [-0.018,  -0.042] | 1.045e-06 |
| Boosted Rate 2 Months Previous | -0.013[0.006,  -0.032] | 0.1903566 |
| Vaccination Rate 2 Months Previous | -0.045[-0.030,  -0.061] | 1.022e-08 |

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| **Table e2: Standardized Regression Coefficients** | | |
| **Variable** | **Coefficient** | **P-value** |
| Relative Humidity 2 Months Previous | -0.294 [-0.189, -0.398] | 3.3e-8 |
| Stringency Index 2 Months Previous | -0.099 [0.079, -0.277] | 0.28 |
| Mask Mandates 2 Months Previous | -0.166 [-0.087, -0.245] | 3.7e-5 |
| Mobility Reduction 2 Months Previous | -0.303 [-0.056, -0.549] | 0.0160825 |
| Cumulative Cases Per 330M people 3 Months Previous | -1.29 [-1.00, -1.58] | < 2.2e-16 |
| Deviation from 68 Fahrenheit 2 Months Previous | -0.044 [0.083, -0.172] | 0.497 |
| Covid Deaths Per 330 Million 2 Months Previous | -0.129 [-0.071, -0.187] | 1.601e-05 |
| Fahrenheit Temperature 2 Months Previous | -0.518 [-0.310, -0.725] | 1.045e-06 |
| Boosted Rate 2 Months Previous | -0.090 [0.045, -0.224] | 0.190 |
| Vaccination Rate 2 Months Previous | -1.11 [-0.729, -1.49] | 1.022e-08 |

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| **Table 1: Summary Statistics of Regression Variables** | | | | |
| **Variable** | **Mean** | **Std** | **Max** | **Min** |
| Relative Humidity | 67.6% | 14.5% | 91.1% | 14.4% |
| Stringency Index | 50.5 | 15.3 | 92.8 | 23.1 |
| Mask Mandates | 0.41 | 0.48 | 1 | 0 |
| Mobility Reduction | 8.5% | 12.1% | 59.0% | -28.0% |
| Cumulative Cases Per 330M people | 2.07e7 | 1.75e7 | 7.40e7 | 0 |
| Fahrenheit Temperature | 59.4 | 17.1 | 96.0 | 7.7 |
| Deviation from 68 Fahrenheit | 15.1 | 11.9 | 60.3 | 0 |
| Boosted Rate | 2.2% | 7.0% | 43.1% | 0 |
| Vaccination Rate | 20.0% | 24.5% | 75.7% | 0 |
| Excess Death Rate | 17.7% | 15.6% | 105.3% | 0 |
| Covid Deaths Per 330M people | 3.83e5 | 3.39e5 | 2.02e6 | 0 |