Journal of Environmental Management 291 (2021) 112662

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: http://www.elsevier.com/locate/jenvman

Research article

Health impacts of daily weather fluctuations: Empirical evidence from COVID-19 in U.S. counties

Lotanna E. Emediegwu

Department of Economics, University of Manchester, Oxford Road, M13 9PL, Manchester, UK

A R T I C L E I N F O

Keywords:
COVID-19
Humidity
Temperature
U.S.
Wind speed

A B S T R A C T

The emergence of the novel coronavirus has necessitated immense research efforts to understand how several non-environmental and environmental factors affect transmission. With the United States leading the path in terms of case incidence, it is important to investigate how weather variables influence the spread of the disease in the country. This paper assembles a detailed and comprehensive dataset comprising COVID-19 cases and climatological variables for all counties in the continental U.S. and uses a developed econometric approach to estimate the causal effect of certain weather factors on the growth rate of infection. The results indicate a non-linear and significant negative relationship between the individual weather measures and the growth rate of COVID-19 in the U.S. Specifically, the paper finds that a 1 °C rise in daily temperature will reduce daily covid growth rate in the U.S. by approximately 6 percent in the following week, while a marginal increase in relative humidity reduces the same outcome by 1 percent over a similar period. In comparison, a 1 m/s increase in daily wind speed will bring about an 8 percent drop in daily growth rate of COVID-19 in the country. These results differ by location and are robust to several sensitivity checks, so large deviations are unexpected.

1. Introduction

COVID-19[1] is the worst pandemic that has hit humankind since the last Century. Since its discovery in Wuhan, China, in December 2020 (WHO, 2020), there have been more than 72.3 million cases, with 1.61 million deaths worldwide, according to John Hopkins University.[2,3] Of this count, the U.S. leads in both the number of cases ($>$ 20%) and deaths ($>$ 18%). Due to the novelty of the virus, there is a plethora of emerging research investigating its genesis and growth, both locally and globally. Mounting evidence attributes the slowed growth of covid infection to endogenous, non-pharmaceutical interventions (NPIs) (e.g., Hsiang et al., 2020), fear-driven behavioral change (e.g., Chernozhukov et al., 2021), media influence (e.g., Bursztyn et al., 2020), amongst others. On the other hand, few studies have detailed how some exogenous factors, such as weather changes, have influenced the number of covid cases, with no unanimity on whether and which environmental factors affect coronavirus transmission.

It might not be coincidental that both severe acute respiratory syndrome (SARS) and covid diseases originated in winter months. Evidence from research on previous epidemics and contagious diseases reveals that weather affects infection rate of infectious diseases. Tan et al. (2005); Bi et al. (2007) document temperature rise as a strong factor that led to the decline in SARS infection. Importantly, the organism causing SARS (SARS-Cov) and covid (SARS-CoV-2) infect humans using similar receptor (angiotensin-converting enzyme 2 (ACE2)) (Runkle et al., 2020). Besides, a dyad of studies, Barreca and Shimshack (2012); Deschênes and Greenstone (2011), use mortality and daily weather changes from U.S. counties to show that annual weather fluctuations, especially temperature and humidity, significantly influence mortality from infectious diseases such as influenza. Recent studies have linked the spike in Spanish flu deaths to declining temperature and torrential rainfall (More et al., 2020).[4] Further, there is documentation that

E-mail address: lotanna.emediegwu@manchester.ac.uk.
URL: https://sites.google.com/view/lotannaemediegwu.

[1] Everywhere else, I shall refer to the disease as covid or coronavirus.
[2] This cumulative statistics are as of 14th December 2020, with 191 countries already infected.
[3] See, Bashir et al. (2020a) for a review of socioeconomic and environmental impacts of Covid-19.
[4] Also, a newly funded NOAA project suggests that the 1918/1919 El Niño is linked to the Flu pandemic.

https://doi.org/10.1016/j.jenvman.2021.112662
Received 9 January 2021; Received in revised form 10 April 2021; Accepted 14 April 2021
Available online 24 April 2021
0301-4797/

weather patterns affect the viability, activity, and transmission efficiency of viruses,[5] hence there is need for more extensive discussion on how and which environmental variables influence coronavirus activities. The few available studies are mostly outside the U.S. with mixed results.

Using a mechanism-based parameterization scheme, Lin et al. (2020) observe that transmission rate of covid in China shows a negative and exponential temperature dependence, while there is no significant relationship with other weather variables. Further Chinese studies like Liu et al. (2020); Oliveiros et al. (2020) reach similar conclusions. On their part, Ma et al. (2020) find that a 1 unit rise in both temperature and absolute humidity will decrease China's covid death count in lag 3 and lag 5 periods, with the greatest decrease both in lag 3. Other country-based studies have also reported similar results. Using statistical methods, Rosario et al. (2020) evidence that the incidence of coronavirus in Brazil is negatively correlated with solar radiation (-0.609, $p < 0.01$), (maximum and average) temperature, and wind speed ($p < 0.01$). Two global studies - Sarkodie and Owusu (2020); Sobral et al. (2020) - that investigate the impact of weather factors of covid find that temperature reduces covid case counts: however, they differ on the effect of rainfall. Sarkodie and Owusu (2020) find that rainfall increases covid caseload, whereas Sobral et al. (2020) observe no effect. On the contrary, a meta-review analysis by Bilal et al. (2020) fails to find a significant association between the pandemic and temperature.

It is important to understand the environment's role in modifying covid transmission activities in the U.S. since it has the largest share of infection worldwide. Few studies have attempted to undertake this exercise. Bashir et al. (2020b) use statistical correlation tools and found that temperature is positively associated with covid cases in New York City. On the other hand, Runkle et al. (2020) employ a case-crossover design with a distributed lag nonlinear model to evaluate how humidity and temperature impact covid cases in 5 U.S. cities. They find that humidity outperforms temperature in reducing covid cases, although both have a non-linear relationship with cases. Using several statistical techniques, Bashir et al. (2021) find that temperature, humidity, environmental quality index, PM2.5, and rainfall are significant factors related to the COVID-19 pandemic in the top 10 most affected states of the USA.

Given the lack of detailed and robust analysis of how meteorological factors affect covid in the U.S., this is the first study, to the best of the author's knowledge, that uses county-level data to empirically demonstrate how weather factors affect growth rate of covid infection. While the existing few studies consider a subset of U.S. cities using raw case counts, this study takes a holistic approach by considering all covid-affected U.S. counties. The weather data are gathered from more than 1000 weather stations all over the U.S., while the covid data is from the New York Times. In addition to the different weather measures employed and the covid index used, the sample's temporal length ensures that the study captures the weather variations in a typical year other than just occurrences in a limited part of the year as done in previous studies. Furthermore, using the entire continental U.S. rather than only a single state or few cities allows for substantial heterogeneity in the model employed in this work.

I apply similar methodology that has been used in previous climate-related studies to estimate the impact of local weather conditions on several economic outcomes.[6] Specifically, I estimate the impact of weather variation on covid infections. These impacts are identified from weakly exogenous and random daily local weather fluctuations, which reduce the problem of omitted variable bias. Moreover, the use of state-by-day fixed effects, which is missing in previous U.S. studies controls for differentials across states that may impact health in a county.

The results in a concise form indicate the existence of a non-linear, negative relationship between weather shocks and growth rate of covid infection in the U.S. Increased weather occurrence lowers cumulative daily growth rate of covid cases over the following week. Specifically, a 1 °C increase in daily average temperature reduces daily growth rate of covid cases by approximately 6 percent. Cumulative daily growth rate of covid cases in the U.S. will fall by 1 percent from a 1 percent increase in relative humidity. Also, a 1 m/s rise in daily wind speed will reduce the outcome variable by 8 percent. More so, these estimates are insensitive to different modifications.

While the results are intuitive and indicative of how daily weather fluctuations affect covid growth rate in U.S. counties, there are some caveats to state. First, the method employed here does not account for changes in behavior following either the pandemic or weather variations, so what is examined here is "short-term" effect. It is expected that changes in human behavior due to climate change (Stankuniene et al., 2020) might alter how weather affects diseases as in Deschenes and Moretti (2009); Deschenes (2014).[7] Hence, the estimated result should be seen as an upper-bound possibility. Also, the paper could not investigate the heterogeneous effect of weather on covid growth rate across age, race, and sex due to data unavailability. It is important to note that although the metrics used in this study are widely accepted in academic and policy circles (The Royal Society, 2020; Chernozhukov et al., 2021), other metrics, such as reproduction rate, also contain important information about the progress of the pandemic. While no one metrics is better than the other, no (single) one provides sufficient information for policy purposes (UK Government, 2020). Hence both rates are always considered for a better understanding of the pandemic. Unfortunately, I am unable to calculate reproduction rate since it requires more sophisticated information, such as the period between each generation of infections, which is unavailable for most counties and some states. Regardless of the caveats, this work complements the growing literature seeking to understand the weather-covid nexus better.

The remainder of the paper is subdivided as follows: Section 2 considers a concise précis of the relationship between weather variables and infectious diseases. Data and methodology are described in Section 3, while the various results are discussed in Section 4. The paper ends with some concluding remarks in Section 5.

2. Weather and infectious diseases - potential mechanisms and channels

There is documented evidence on how weather affects the transmission of infectious diseases (see, Sellers, 1980; Patz et al., 1996; Altizer et al., 2006; Barreca and Shimshack, 2012, for some overview). Weather affects the ability of pathogens to transit from person to person. Also, some or all of the cycle of infection - the population of pathogens and hosts, and the interactions between them (Avery et al., 2020) - could be affected by nature. Research has shown that high temperature reduces viruses' viability and activity; very cold temperature makes it difficult for them to replicate, thereby lowering the viral load in the atmosphere (Polgreen and Polgreen, 2018). Besides, cold temperature increases sneezing and coughing, both of which are effective and fast mediums of transmitting contagious diseases. Further, cold air can irritate the airways and lungs, thereby causing breathing to be more strenuous and making the use of NPIs like face mask difficult to sustain

[5] See, Campbell et al. (2013) (Dengue virus), Soverow et al. (2009) (West Nile virus), Woodruff et al. (2002) (Ross River virus). For a detailed analysis of the interplay amongst weather, viruses, and host, see Sellers (1980).

[6] Some previous climate-related studies include Kalkuhl and Wenz (2020); Dell et al. (2012) (economic growth); Harari and Ferrara (2018); Hsiang et al. (2013) (conflict); Deschênes and Greenstone (2007); Hsiang and Meng (2015) (agriculture); Deschenes and Moretti (2009); Barreca (2012) (mortality).

[7] Streimikiene et al. (2020), in a systematic review, show that behavioral changes following climate change could affect households' energy consumption, which is an important medium of conditioning atmospheric conditions to extenuate or exacerbate viral infections.

in such conditions.

Humidity is economically important as it affects human health *via* different mechanisms. Low humidity means less water content in the air, therefore making aerosols smaller. This condition can also lead to dehydration, promoting the spread of airborne diseases, like covid, due to prolonged activity of suspended infectious aerosols in the air. On the other hand, a moist atmosphere means that the aerosols are larger and fall to the ground much quicker. Further, some studies suggest that host resistance to viruses are low under dry air condition. For example, in a laboratory experiment, Kudo et al. (2019) observe that mice with influenza at 10% relative humidity level had more symptoms and are more likely to die than those at 50%. Equally important, high humidity causes sweating, making the cooling of the human body more difficult (Hsiang and Kopp, 2018). Besides, it can impair the respiratory system because it abets the spread of non-viral organisms like bacteria, fungi, and dust mites (Barreca, 2012).

Wind speed is also important in understanding the spread of (airborne) infectious diseases such as coronavirus (Morawska and Milton, 2020). Wind speed may modulate the dynamics of various pathogens and vectors (Ellwanger and Chies, 2018), and low wind speed increases the spread of infectious disease (Altizer et al., 2006). Infectious aerosols can stay for some hours on surfaces and atmosphere - up to 3 h in aerosols, 4 h on copper, 24 h on cardboard, and 2–3 days on plastic and stainless steel (van Doremalen et al., 2020). However, these times are reduced with high wind speed.

Summarily, since weather variables are correlated, I set up the empirical specification to include all relevant weather measures. Also, the paper includes weather measures' quadratic terms to account for potential non-linearity, which is conventional in the climate-health literature.

3. Data and model specification

3.1. Data sources and description

3.1.1. Covid and population data

I draw county-level covid data from New York Times.[8] Among other county-level variables, the dataset contains the daily count of covid cases from January 21, 2020 and is updated daily as new information becomes available.,[9, 10] The sample, however, ends on October 31, 2020. The dataset is obtained from daily officially reported confirmed case counts reported to the Centers for Disease Control and Prevention (CDC). The initial sample contains 3106 counties covering the continental 48 U.S. states, including the District of Columbia, totaling 885,210 county-day observations.[11]

3.1.2. Weather data

The paper uses average temperature, total precipitation, average relative humidity, and average wind speed from more than 1000 operational weather stations in the United States during the sample period to measure daily weather fluctuations. These data are obtained from the National Climatic Data Center "Cooperative (or Global Surface) Summary of the Day" (GSOD) files using geospatial software. The GSOD records detailed daily weather information by weather stations from 1928 till present. It is a very reliable dataset used by many weather data services such as the Parameter-Elevation Regressions on Independent Slopes Model (PRISM), NASA, *etc.* The construction and aggregation of the weather dataset are described, with more details, in the Supplementary Information. For the purpose of weighting, I use estimated 2018 county-level population from the United States Census Bureau.[12]

3.2. Summary statistics

The paper reports the summary statistics of the variables at regional and national levels in Table 1. The first four rows contain regional statistics, while the national statistics are in the last row.

The national mean temperature over the sample period is 17.39 °C. The average temperature over the same period varies across regions, showing some form of spatial variation - from 13.43 °C in the Midwest to 20.56 °C in the South. Also, there is significant within variation across the regions, as seen from the standard deviations. The West region has the lowest relative humidity, 49%, which means that, on average, air in the region is less moist than in other regions where the relative humidity is above the national average. Table 1 also shows that wind speed is highest in the Midwest and lowest in the Northeast, with a national average of 3.09 m/s.

Fig. 1 further reveals the geographical variation in weather measures in the U.S. The maps show that some parts of the South are both hot and very humid, whereas average wind speed is highest in the Midwest. Fig. 2 also displays the temporal variation in the weather variables across regions. These spatial and temporal variations are the basis for using these weather variables to predict changes in growth rate of covid infection.

Fig. 3 shows the geographical distribution of cumulative covid cases in the U.S., as of October 31, 2020. There appears to be some relationship between cumulative cases and weather measures, as the largest incidence of covid infection occurs in the colder and less windy regions of the U.S. - Northeast and West regions.

3.3. Econometric strategy

This paper seeks to estimate the effect of weather on the covid pandemic in the U.S. The motivation for the model follows Chernozhukov et al. (2021) intuition on the popular epidemiology model for infectious disease known as Susceptible–Infected–Recovered–Dead (SIRD).[13] First, I describe the outcome variable - growth rate of infection (GRI) as

$$GRI_{it} = log(C_{it}) - log(C_{it-7})$$

where *Cit* refers to cumulative covid cases in county *i* at time *t*. *GRI* measures the rate at which infection is transmitted amongst the populace, and it is lagged by a week to account for the period between when an infection *occurs* and when a positive test *detects* it. Technically, $C_{it} - C_{it-7}$ refers to the number of new covid cases in the last seven days. The use of growth rate rather than covid count is based on policy preference, as the former is one of the main metrics which policymakers use to

[8] Data is accessible *via* https://github.com/nytimes/covid-19-data/blob/master/us-counties.csv.

[9] The first reported case in the USA was on 20th January 2020 in Washington state.

[10] Confirmed cases refer to counts of individuals whose coronavirus infections were confirmed by a molecular laboratory test. Therefore, such statistics are widely considered to be an undercount of the true toll. However, this is not considered to be a serious problem as there is no evidence in the literature that such bias systematically correlates with county-level weather fluctuations. Moreover, Hsiang et al. (2020) find the bias associated with such under-reporting is quantitatively small.

[11] I excluded Alaska, Hawaii, and observations from unspecified counties.

[12] https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-detail.html

[13] The standard Susceptible–Infected–Recovered (SIR) model compartmentalize economic agents into three states as suggested by the name. Agents can move between states *via* two ways: an infectious agent becomes noninfectious and moves to recovered state, or a susceptible agent can come in contact with an infectious agent, become infected, and move to the infected state. These movements are controlled by two parameters - recovery rate (γ) and the number of people that would be infected by an infectious agent ($R0$). For more on this model, the reader is referred to Avery et al. (2020).

Table 1
Summary statistics of weather measures across regions.

	Average Temperature (° C)				Relative Humidity (%)				Wind Speed (m/s)			
	Mean	Min	Max	StD	Mean	Min	Max	StD	Mean	Min	Max	StD
Midwest	13.43	−27.67	32.74	9.72	68.21	15.38	100	12.50	3.56	0.08	13.41	1.54
Northeast	14.24	−20.67	31.09	8.72	66.13	19.69	99.39	14.11	2.87	0.14	11.06	1.23
South	20.56	−8.71	36.6	7.37	70.51	7.10	100	13.31	2.96	0	16.83	1.41
West	18.02	−24.24	42.12	8.33	49.44	6.23	99.42	20.30	3.02	0	16.64	1.19
USA	17.39	−27.67	42.12	8.88	64.35	6.23	100	17.37	3.09	0	16.83	1.39

Note: The above table represents 285 daily observations (from January 21 to October 31, 2020) for 3106 counties spanning the country's census regions. Census regions are defined as follow: Midwest (IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI), Northeast (CT, MA, ME, NH, NJ, NY, PA, RI, VT), South (AL, AR, DC, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV), and West (AZ, CA, CO, ID, MT, NM, NV, OR, UT, WA, WY). StD denotes standard deviation. Observations are weighted by county-level population.

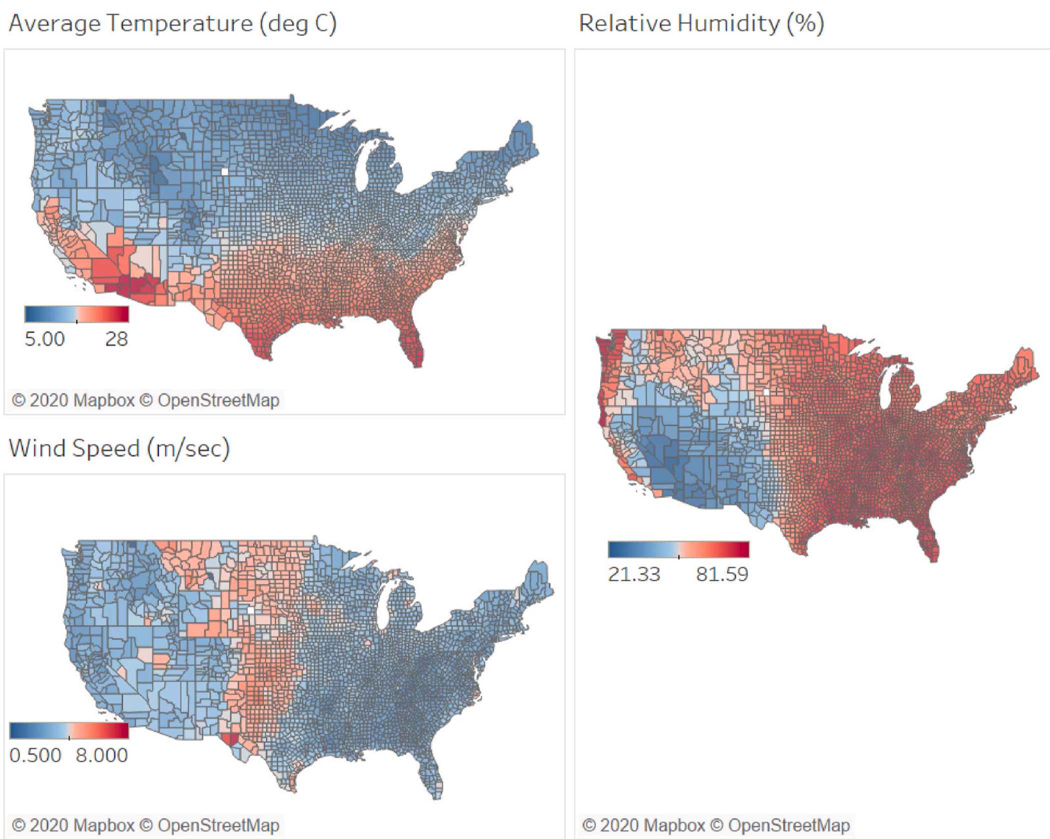


Fig. 1. Spatial variation of average weather conditions in the U.S. (January 21 - October 31, 2020).

decide what sort of policy to adopt (UK Government, 2020). There is no unanimity on the number of lag days to use in calculating growth rate. Here, I choose 7-day lag period because laboratory and statistical experiments suggest that the incubation period of covid volleys between 5 and 7 days (see, Lauer et al., 2020; Li et al., 2020; Wu et al., 2020). However, the insensitivity of the results to different choices of lag lengths is shown in the Supplementary Information. Further, I do not smoothen the data so as not to lose significant variations. Although I show in the robustness section that smoothening the data produces similar estimates.

Due to the lag time between infection and detection, the paper estimates weather variables' impact using their lags. Specifically, I construct a panel data model at county/day level that takes the reduced form

$$GRI_{it} = \alpha_c + \gamma_s t + \sum_{j=7}^{j=13} \beta_j^{T} T_{it-j} + \sum_{j=7}^{j=13} \beta_j^{RH} RH_{it-j} + \sum_{j=7}^{j=13} \beta_j^{WDSP} WDSP_{it-j} + \sum_{j=7}^{j=13} \beta_j^{PREP} PREP_{it-j} + \varepsilon_{it} \tag{1}$$

where *GRIit* refers to a vector of outcomes - growth rates of infection - in county i for day t, α_c are county fixed effects to control for county-specific time-invariant determinants of covid outcomes such as geographical location, $\gamma_s t$ are state-by-year fixed effects which accounts for time-varying factors of mortality that are common within a state (state-wide lockdowns, for example). ε_{it} are idiosyncratic errors.

T_{it-j}, RH_{it-j}, $WDSP_{it-j}$, and $PREP_{it-j}$ represent daily average temperature (in °C), average relative humidity (in %), average wind speed (in m/s), and aggregate rainfall (in mm), respectively, observed on day *t-j* in county i. The common expectation is that any disruption of infection activities due to weather actions will be realized after some time, ergo

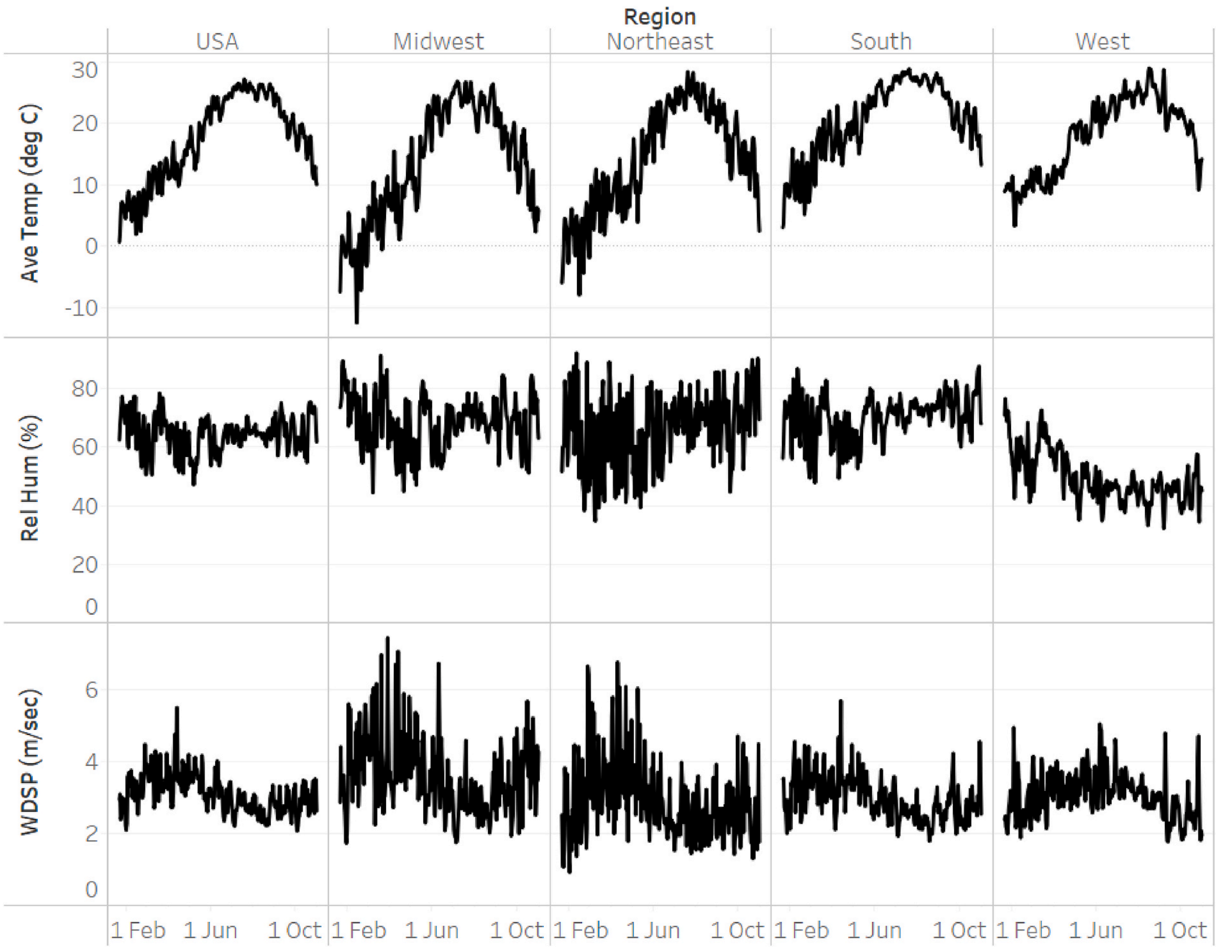
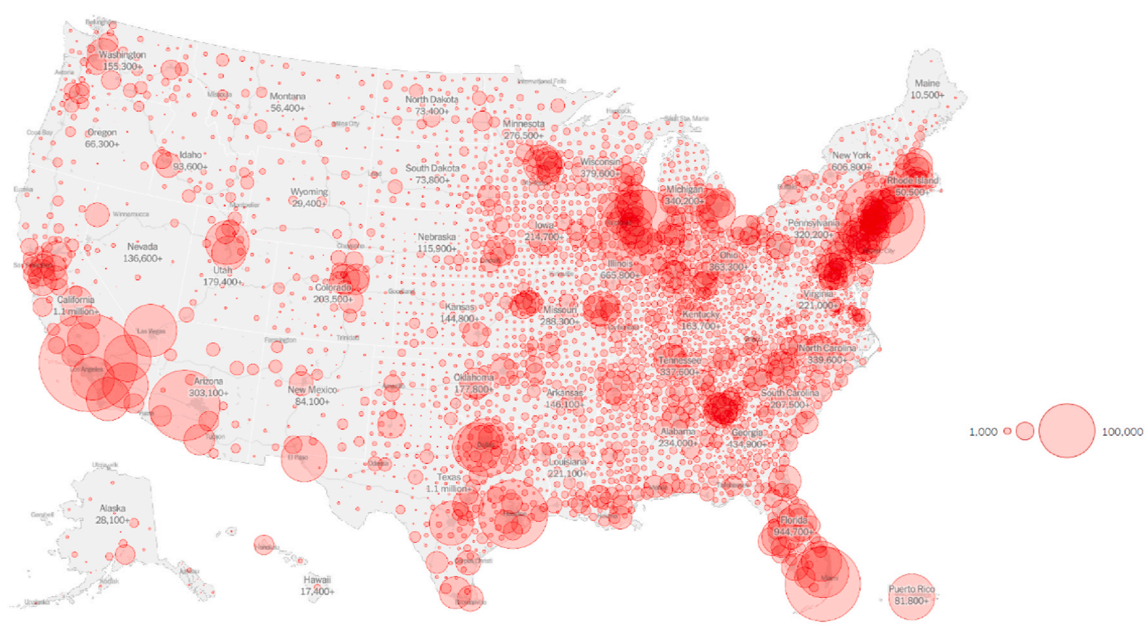


Fig. 2. Average weather trends by region.



Source: `https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html`

Fig. 3. U.S. Total COVID-19 reported cases as at October 31, 2020. *Source:* *https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html*

the main explanatory variables capture the weather events of seven days (or one week) preceding the week the outcome variable captures. As is customary in dynamic models (see, Dell et al., 2012), this paper is interested in the cumulative effect of the lag structure, which represents the growth effect of weather fluctuations.

Since weather variables are mostly correlated, the non-inclusion of an important weather variable can produce biased results, except if the relationship amongst the variables is uniform across counties, which is not so in this case, as seen in Fig. 1. Hence, joint estimation of the weather variables accounts for the correlation among them. The paper does include precipitation as a customary practice but do not report the results because (i) there is little spatial variation in precipitation as seen in Figure S2 in the Supplementary Information, and (ii) previous mortality-climate studies for the U.S. confirm that the impact of rainfall on health outcomes in the U.S. is insignificant due to reason (i) (Deschênes and Greenstone, 2011; Barreca, 2012).

I intend to use the variation inherent in these weather measures to capture accurate empirical estimates. In keeping with the convention in climate studies, this study includes the quadratic terms of the weather measures to capture potential non-linearities. Moreover, I do not add other controls to avoid the *bad control* scenario (Angrist and Pischke, 2008; Dell et al., 2014). ε_{it} are clustered at county-level to account for possible correlation of the standard error terms within county groups.

The reason for having a full set of county and state-by-day fixed effects is to ensure that the derived estimates are truly from fluctuations in weather. This is a fair assumption, given that weather fluctuations are fairly exogenous to other unobserved mortality factors. Also, to account for heteroskedasticity associated with county sizes, a weighted version of equation (1) is estimated where weight is the square root of county-level population. In addition to controlling for heteroskedasticity, population-weighted models allow us to estimate impacts on average person rather than average county. The work also considers models weighted with other important population subgroups and socio-economic indices in the Supplementary Information, which produce broadly identical results.

4. Empirical results and discussion

4.1. Main results

In this section, I discuss the results obtained from fitting several versions of equation (1). Table 2 presents the point estimates associated with the impact of daily weather variations on daily cumulative growth rate of covid infection in the U.S. The estimates presented here are the cumulative effects of lagged weather variables on the outcome, which signifies the growth effect of weather fluctuations. Due to space constraints, the estimates of the individual lags' effects are reserved in the Supplementary Information. The linear terms define the marginal effect of weather changes evaluated at the mean value, whereas the quadratic terms reflect the marginal effect's behavior as one deviates from the center.

Table 2
Main specification results.

	(I)Temp	(II)Temp + RH	(III)Temp + RH + Wind
Temp. cum	−0.059	−0.055	−0.057
	[0.003]***	[0.003]***	[0.003]***
Temp. cum sq	0.001	0.001	0.001
	[0.000]***	[0.000]***	[0.000]***
RH cum		−0.011	−0.013
		[0.003]***	[0.003]***
RH cum sq		0.000	0.000
		[0.000]***	[0.000]***
WDSP cum			−0.084
			[0.007]***
WDSP cum sq			0.005
			[0.001]***
Observations	636,595	633,170	633,082
Counties	3094	3094	3093

Notes: All specifications include county FE, state × day FE and are weighted by the county-level population. Robust standard errors are in parentheses, adjusted for clustering at county level. Temperature is in degrees Celsius (° C), relative humidity in percentage (%), and wind speed is in meters per sec (m/s). Outcome variable is growth rate of infection (GRI).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Beginning with temperature effects, Column III in Table 2 shows a significant and negative relationship between temperature and GRI in the U.S. Specifically, an increase of 1 °C in average daily temperature will reduce the GRI by approximately 6% in the following week. This estimate is consistent across specifications, either bivariate (Col I) or multivariate (Cols II and III). Similarly, the paper finds a negative and significant relationship between relative humidity and GRI in the U.S. A 1% rise in relative humidity would lead to a 1% drop in GRI, which signifies that areas with increasing relative humidity levels will experience a reduction in cumulative growth rate of covid cases in the ensuing week. Furthermore, the main result suggests that high wind speed will lower growth rate of covid infection. Explicitly, a 1 m/s (or 2.2 miles per hour) increase in average daily wind speed will necessitate an 8% drop in GRI in the subsequent week.

The findings in this paper also complement the results from Lin et al. (2020); Liu et al. (2020), who reach similar conclusions of a negative relationship between temperature and covid infection in China. However, they contrast Bashir et al. (2020b), who find a positive relationship between temperature and covid caseload in New York. Additionally, as presented in the results, the importance of moist air is corroborated by similar conclusions from some studies such as Ma et al. (2020); Runkle et al. (2020). However, this work differs from these studies in terms of methodology, sample size, and temporal coverage as discussed in the previous section. The negative relationship between wind speed and GRI indicates the importance of wind in reducing covid infections. It implies that, *ceteris paribus,* more windy counties/states will experience decline in cumulative infection growth rate.

The quadratic terms of the weather variables are significant, which indicate a potential non-linear (convex by nature) relationship between weather factors and the covid outcome - GRI. Such non-linearity means there is a minimally beneficial level from which the effects start rising, significantly or insignificantly, in both directions. The non-linear observation is similar to the findings in Deschênes and Greenstone (2011); Prata et al. (2020) (for temperature) and Barreca (2012); Runkle et al. (2020) (for humidity).

4.2. Robustness results

The paper considers several robustness checks to ascertain the sensitivity of the main results. The robustness tests entail re-modeling equation (1) with different panel samples, without outliers, with lower frequency data and smoothening effects.[14]

4.2.1. Different start dates

The first row in Table 3 shows the results for re-estimating equation (1) with trimmed sample sizes. The results show a steady negative effect, howbeit a decline in the size of the coefficients as the sample is trimmed down from January 21 to April 1. The reduction in the estimates' magnitude could be due to the loss of more than 30% of the original sample size on April 1. Also, starting the sample from April 1 means some loss of variation in weather observations since, for example, temperature has begun to fall by June, as shown in Fig. 2.

[14] Results of further robustness tests can be found in the Supplementary Information.

Table 3
Robustness results.

		Temperature	Relative humidity	Wind speed
Different Start Dates (I)	February 1	−0.057 [0.003]***	−0.013 [0.003]***	−0.084 [0.007] ***
	April 1	−0.041 [0.001]***	−0.007 [0.001]***	−0.050 [0.004] ***
Outliers Influence (II)	Exclude CA	−0.056 [0.003]***	−0.015 [0.003]***	−0.075 [0.006] ***
	Exclude CA & FL	−0.058 [0.003]***	−0.015 [0.003]***	−0.064 [0.006] ***
Lower Frequency (III)	Weekly	−0.073 [0.005]***	−0.019 [0.003]***	−0.141 [0.017] ***
	Monthly	−0.133 [0.007]***	−0.033 [0.004]***	−0.101 [0.036] ***
Smoothening (IV)	3-MvA	−0.055 [0.003]***	−0.011 [0.003]***	−0.078 [0.006] ***
	7-MvA	−0.053 [0.003]***	−0.009 [0.002]***	−0.074 [0.005] ***
Baseline		−0.057 [0.003]***	−0.011 [0.003]***	−0.084 [0.007] ***

Notes: All specifications include county FE, state × day FE and are weighted by the county-level population. Robust standard errors are in parentheses, adjusted for clustering at county level. Temperature is in degrees Celsius(^{o} C), relative humidity in percentage (%), and wind speed is in meters per sec (m/s). Outcome variable is growth rate of infection (GRI). For lower frequency analysis, weekly covid data is lagged by one week, whereas the weather data by two weeks. Monthly data is lagged by one month. See in-text for more details.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.2.2. *Outliers influence*

To confirm that the results are not driven by states with very high cases of covid infections, I purge the sample data of all counties in the two states with the highest cumulative covid cases as of October 31 - California and Florida. Row 2 in Table 3 shows that the states with large cases do not principally drive the results as the estimates are still very similar to the baseline results.

4.2.3. *Lower frequency data*

Further, I test if the main estimates are due to noise by re-analyzing equation (1) with lower frequency data. I aggregate the covid cases while averaging weather measures to (i) weekly and (ii) monthly levels. The results displayed in Row 3 of Table 3 show similar significant signs as the baseline, however with larger estimates. The large coefficients are not surprising given the use of lower frequency data in this scenario.

4.2.4. *Smoothening effect*

Next, the paper subjects the baseline model to smoothening test using two moving averages: 3-day, 7-day. I use these moving averages to smoothen the covid data before deriving the growth rate of infection index. Row 4 shows that the results are not principally affected by smoothening as they appear to be very stable across specifications.

Overall, the alterations to the baseline specification do not significantly alter the estimated impact of daily weather fluctuations on cumulative daily growth rate of covid infections in the U.S.

4.3. *Investigating channels and sources*

Next, the research investigates if there are particular areas in the country where the impacts of environmental factors on covid are greater. I start by showing the results of the estimated model specific to each (i) region (ii) division (iii) hot/cold area, and (iv) state in the U.S.

Table 4 shows that every region will benefit from temperature rise; however, the impact is more noticeable in the Northeast and South than in other regions. The large point estimates associated with both regions imply that reduction in the growth rate of infection is highest in areas with extreme temperatures. On the other hand, there is more heterogeneity in the impact of relative humidity and wind speed. An increase in relative humidity will reduce GRI in the South and the Northeast regions. These regions possess higher relative humidity than other regions, as seen in Fig. 1. Similarly, the impact of a marginal rise in wind speed is not uniform across regions. Its effect is positive in the Northeast where wind speed is the lowest and negative in other regions with high average wind speed.

Similarly, the second column in Table 4 shows that the largest negative impacts of temperature are found in divisions within regions with extreme temperatures. For example, South Atlantic and West South Central divisions are in the South region while New England and Middle Atlantic divisions are in the Northeast region. Divisions with mild temperatures may not experience as much decline as those in cooler and very hot regions. Relative humidity also exhibits similar heterogeneous trends as in the regional analysis. Divisions in high humid areas benefit more from a further humidity increase. On the other hand, the effect of a

Table 4
Regression by location.

		Temperature	Relative humidity	Wind speed
Region	South	−0.114 [0.005]***	−0.021 [0.004]***	−0.070 [0.012]***
	West	−0.064 [0.004]***	0.007 [0.003]**	−0.199 [0.029]***
	Northeast	−0.138 [0.009]***	−0.081 [0.010]***	0.090 [0.029]***
	Midwest	−0.044 [0.006]***	0.003 [0.004]	−0.102 [0.010]***
Division	Mountain	−0.044 [0.004]***	0.004 [0.004]	−0.201 [0.040]***
	New England	−0.143 [0.019]***	−0.072 [0.018]***	0.041 [0.061]
	Middle Atlantic	−0.140 [0.007]***	−0.096 [0.013]***	0.102 [0.038]***
	East North Central	−0.053 [0.014]***	0.054 [0.006]***	−0.121 [0.020]***
	West North Central	−0.037 [0.002]***	−0.021 [0.004]***	−0.021 [0.012]*
	Pacific	−0.117 [0.013]***	0.018 [0.007]**	−0.216 [0.054]***
	South Atlantic	−0.120 [0.009]***	0.019 [0.005]***	−0.136 [0.032]***
	East South Central	−0.098 [0.008]***	0.048 [0.011]***	−0.146 [0.024]***
	West South Central	−0.104 [0.005]***	−0.036 [0.009]***	0.042 [0.012]***
Hotness	Yes	−0.114 [0.006]***	−0.008 [0.004]**	−0.071 [0.011]***
	No	−0.064 [0.004]***	−0.019 [0.002]***	−0.117 [0.009]***

Notes: All specifications include county FE, state × day FE and are weighted by the county-level population. Robust standard errors are in parentheses, adjusted for clustering at county level. Temperature is in degrees Celsius (^{o} C), relative humidity in percentage (%) and wind speed is in meters per sec (m/s). Outcome variable is growth rate of infection (GRI).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

further rise in humidity is positive in low humidity divisions like East North Central, and Pacific. The impact of increasing wind speed is generally negative in all divisions except New England, Middle Atlantic, and West South Central, where wind speed is very low.

To further explore the source of the relationship, I divide all counties into two groups based on how hot they are relative to the U.S. median temperature. A county is classified as "hot" if its median temperature is above the national median; otherwise, it is classified as "cold". After, the baseline equation is re-estimated separately for both groups. The results, displayed in Column 3, show that the beneficial effect of a further temperature rise is higher in hot counties than in cold counties. Specifically, hot counties are, on average, twice more likely to experience a reduction in GRI from a 1 °C temperature rise than their cold counterparts. On the contrary, the impacts of a marginal increase in relative humidity and wind speed are more felt in cooler counties.

To further the assertion of an inverse relationship between daily weather fluctuations and growth rate of covid infection, I re-analyze equation (1) by state. The state regression results in Fig. 4 follow a comparable pattern as the previous sub-national regression results. The states with the highest impact of temperature are in the South and Northeast regions. Relative humidity shows some heterogeneity in terms of effects. States in humid regions benefit from an additional rise in relative humidity than those within low humid regions. Similarly, the impact of wind speed on GRI is higher for states with high wind speed, like Florida and Kentucky. On the contrary, low windy states such as New York and New Jersey may not benefit from a marginal increase in wind speed.

Understanding the impacts of daily local weather fluctuations on covid, plus other socio-economic considerations, will help inform policymakers of the appropriate policies to implement in the fight against covid. While lockdowns, restrictions, and other NPIs are necessary to bend the curve, the enforcement of these measures should be tighter in areas with low temperature, humidity, or wind speed. These containment policies will help reduce the viral load in the atmosphere. Also, given that areas with low wind speed may experience infectious aerosols staying on surfaces for longer hours, sanitization of surfaces should be prioritized in these areas. As the race to get as much people vaccinated is on, the need to recognize priority people, periods, and places is important. Governments should not only focus on getting the jab into vulnerable people's or critical workers' arms but also target areas where the transmission tends to be more rapid due to prevailing weather conditions.

5. Conclusion

This study investigates how environmental factors affect the growth rate of COVID-19 transmission in the country with the highest transmission incidence. The study finds that in addition to changes in human

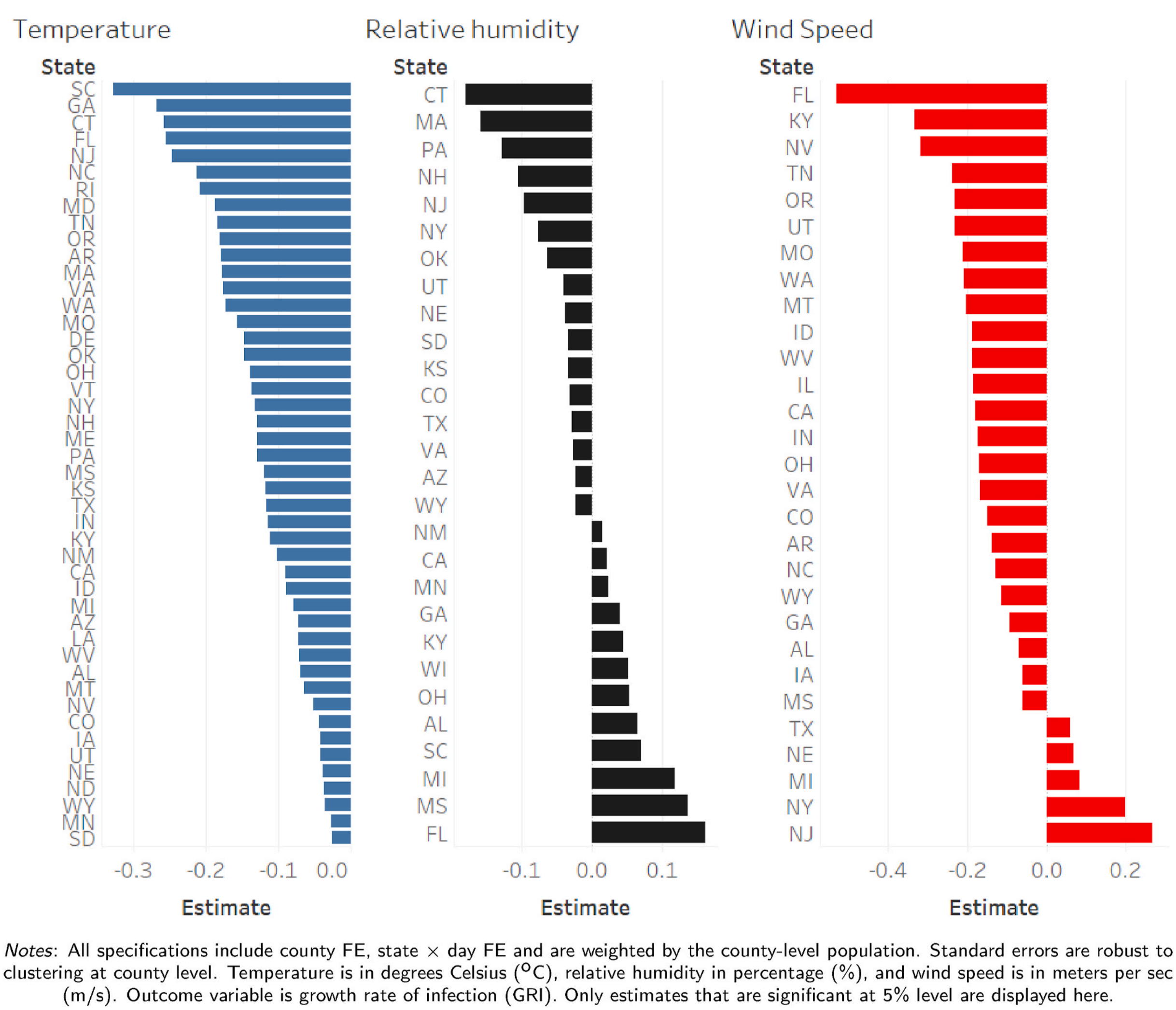


Fig. 4. State Regression Results. *Notes*: All specifications include county FE, state × day FE and are weighted by the county-level population. Standard errors are robust to clustering at county level. Temperature is in degrees Celsius (° C), relative humidity in percentage (%), and wind speed is in meters per sec (m/s). Outcome variable is growth rate of infection (GRI). Only estimates that are significant at 5% level are displayed here.

behavior (Chernozhukov et al., 2021; Chang and Meyerhoefer, 2020) and mandated government policies (restrictions) (Acemoglu et al., 2020; Hsiang et al., 2020), the reduction in GRI could also be linked to unbalance in environmental factors. Specifically, an additional increase in any of the weather measures considered will reduce GRI by a range of 1–8 percent. Also, these effects differ by location. Hot regions benefit more from temperature rise, while cold areas will benefit more from increased humidity and wind speed. The paper fails to accept the null hypothesis by early studies that weather changes do not affect covid outcomes. One reason these studies may have found insignificant estimates could be the use of (early) data with little within weather variation (see, Wooldridge, 2010).

The results in this paper could also inform why countries in tropical regions (e.g., sub-Saharan Africa) report low case count. The intuition follows from Kalkuhl and Wenz (2020); Dell et al. (2012), who show that hot areas tend to be poorer than cold countries, and Adda (2016), who observes that viral infections spread faster during an economic boom. Tying these two pieces together implies the existence of a linkage between weather, wealth, and pandemic. The results, therefore, suggest that warmer (and poorer) countries may experience less growth rate of infection.[15]

The findings do not infer that nature can handle the pandemic more than human interventions. Since weather is exogenous, we cannot rely on its random occurrence to save humanity from the virus. Although weather fluctuations impact GRI, I believe that non-pharmaceutical interventions (NPIs) are more effective in bending the curve (reducing the GRI) due to their endogenous nature. However, while safety measures are very important, the study suggests that they be taken more seriously in places with mild temperature, low humidity, and low wind speed. For example, since infectious aerosols are suspended longer in the atmosphere in low humid and windy areas, mask-wearing should be mandated in such areas to reduce the viral load going into the atmosphere. Besides, the predicted second spike during the winter period suggests that a fall in temperature and humidity could drive up infection rates.

Some limitations to the study are as follow. The paper could not investigate the heterogeneous effect of weather of covid growth rate across age, race, and sex due to data unavailability. It is possible to suspect that the risk of infection will be greater for certain classes such as the elderly (65+), male population, and black and ethnic minorities. For example, a calibrated study by Ferguson et al. (2020) reports that the infection fatality for 80+ population is 9.3%, 2.2% for those aged 60–69, and 0.03% for 20–29.

Furthermore, the impact of certain climatological variables can be conflated with other environmental factors that could not be accounted for in this study. For example, hot weather tends to increase the primary sources of air pollution, and highly polluted areas are prone to higher air transmission of covid (Conticini et al., 2020). In addition, the interaction between the spillover effects from extreme temperatures and high humidity, such as increased mortality (Barreca, 2012; Deschênes and Greenstone, 2011), migration (Zeng and Bao, 2020; Deschenes and Moretti, 2009), and reduction in covid transmission requires further investigation.

Weather fluctuation is one of the largest modifiers of human behavior, affecting the way diseases spread. For example, people generally stay indoors during winter periods, unlike summer seasons, which may suppress the spread of viruses. In like manner, given that cold seasons, such as winter, tend to be associated with rifeness of viral infections like the flu, people may be extrinsically motivated to act cautiously, especially if effectively educated.[16] The above scenarios depict that seasonal weather changes may affect viral spread by modifying human behavior, an area that provides more opportunity for interesting research.

More so, there are more than a thousand confirmed strands of SARS-CoV-2 genome in circulation globally. These strands may differ in life span, viability, and communicability, as communicated in Korber et al. (2020), and may vary in how they respond to weather factors.

As with other empirical models, real-world infection processes are more complicated than what models assume. There is tremendous heterogeneity in several factors that predispose a person to be confirmed as infected, such as degree of exposure, severity of infection, *etc.* It is practically difficult for any single model to answer all the questions or account for all uncertainties. Therefore, this paper contributes to an emerging empirical epidemiological literature that applies econometric techniques to understand the interaction between weather factors and the pandemic's growth rate.

Declaration of competing interest

The author declares that there is no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Much appreciation goes to Ada Wossink and Alastair Hall for their significant comments on this paper's earlier draft. Thanks to two anonymous reviewers and the editor for their useful comments and suggestions. I am grateful to Daniel Nwandu for graciously allowing me to use his big data computer facility in carrying out my analysis. The usual disclaimer applies.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.112662.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

A Supplementary Information

Supplementary information to this article can be found online.

Credit author statement

Lotanna Emediegwu is responsible for every aspect of this work.

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[15] The low case counts recorded in some developing countries could also result from several factors such as myths and misinformation surrounding the pandemic, poor data collection, institutional failures, experience from past pandemics. For example, Emediegwu and Oni (2021) attribute the fewer cases of Covid-19 reported in Africa (compared with the United States and Europe) to lessons learned from the fight against Ebola during the 2014–16 outbreak (predominantly in West Africa).

[16] For example, Ntona et al. (2015) evidence the dominant role environmental education plays in radically changing the patterns of human behavior towards an environmentally sustainable orientation.

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