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Impact of meteorological factors on COVID-19 pandemic: Evidence from top 20 countries with confirmed cases

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ARTICLE INFO

ABSTRACT

The global confirmed cases of COVID-19 have surpassed 7 million with over 400,000 deaths reported. However, 20 out of 187 countries and territories have over 2 million confirmed cases alone, a situation which calls for a critical assessment. The social distancing and preventive measures instituted across countries have a link with spread containment whereas spread containment is associated with meteorological factors. Here, we examine the effect of meteorological factors on COVID-19 health outcomes. We develop conceptual tools with dew/frost point, temperature, disaggregate temperature, wind speed, relative humidity, precipitation and surface pressure against confirmed cases, deaths and recovery cases. Using novel panel estimation techniques, our results find strong evidence of causation between meteorological factors and COVID-19 outcomes. We report that high temperature and high relative humidity reduce the viability, stability, survival and transmission of COVID-19 whereas low temperature, wind speed, dew/frost point, precipitation and surface pressure prolong the activation and infectivity of the virus. Our study demonstrates the importance of applying social distancing and preventive measures to mitigate the global pandemic.

1. Introduction

The novel coronavirus (COVID-19) aka severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has received much attention due to its impact on the environment, socio-economic development and health outcomes (Sarkodie and Owusu, 2020a). The first incidence of COVID-19 occurred in Wuhan city, China which subsequently spread across countries and was declared a global pandemic by the World Health Organization (WHO) (WHO, 2020). As of May 02, 2020 [6:32 a. m. (GMT+2)], 3,344,099 confirmed cases, 238,663 deaths and 1,053, 342 recovery cases had been reported (Lauren, 2020). Several preventive and social distancing measures have been instituted across countries to contain the spread of COVID-19 (Wilder-Smith and Freedman, 2020). These containment measures are somewhat related to reducing the human-to-human transmission of COVID-19 that might have been acquired through carriers driven by meteorological factors (Li et al., 2020). Several studies have thus far examined the relationship between COVID-19 and meteorological factors such as temperature (Ma et al., 2020), humidity (Liu et al., 2020), and air pollution (Zhu et al., 2020). However, there is no single study on other useful meteorological factors such as, *inter alia*, wind speed, dew/frost point, disaggregate

temperature, precipitation and surface pressure. It is reported that COVID-19 has inherent genetic variability that leads to high mutation rates, hence, affecting its adaptation (Martinez, 2020). Thus, assessment of all useful impact of meteorological factors is essential to empirically understand the virus.

Contrary to previous attempts, this study for the first time develops conceptual tools based on novel panel estimation techniques across the top 20 countries with confirmed cases. We expand existing literature to include eight meteorological factors and assess its impact on COVID-19 confirmed cases, deaths and recovery cases. Our empirical results provide new perspectives to understanding the survival, viability, stability and transmission of the virus.

2. Materials & method

The meteorological dataset used in this study were collated from NASA (2020) whereas data on COVID-19 outcomes were collected from John Hopkins COVID-19 realtime data (Lauren, 2020). The daily frequency data were collated from January 22 to April 27, 2020. Using national level data, we construct panel data of top 20 countries namely the US, Spain, Italy, France, United Kingdom, Germany, Turkey, Russia,

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Iran, China, Brazil, Canada, Belgium, Netherlands, India, Switzerland, Peru, Portugal, Ecuador, and Saudi Arabia. The dataset comprises of dew/frost point at 2 m [T2MDEW, measured in °C], maximum temperature at 2 m [T2M_MAX, measured in °C], minimum temperature at 2 m [T2M_MIN, measured in °C], temperature at 2 m [T2M, measured in °C], wind speed at 2 m [WS2M, measured in m/s], precipitation [PRECTOT, measured in mm day-1], relative humidity at 2 m [RH2M, measured in %], surface pressure [PS, measured in kPa], recovered cases [RECOVERED, measured in persons], deaths [DEATHS, measured in persons], and confirmed cases [CONFIRMED, measured in persons]. As of April 27, the reported cumulative recovery (per persons), deaths (per persons) and confirmed (per persons) cases respectively were 111424, 56259, 988197 for the US; 120832, 23521, 229422 for Spain; 66624, 26977, 199414 for Italy; 45513, 23293, 164589 for France; 344, 21092, 157149 for United Kingdom; 114500, 6126, 158758 for Germany; 33791, 2900, 112261 for Turkey; 7346, 794, 87147 for Russia; 70933, 5806, 91472 for Iran; 78374, 4637, 83918 for China; 31142, 4603, 67446 for Brazil; 18268, 2841, 49616 for Canada; 10878, 7207, 46687 for 250, 4518, 38245 for Belgium; 7137, 939, 29451 for the Netherlands; 22200, 1665, 29164 for India; 22200, 1665, 29164 for Switzerland; 8425, 782, 28699 for Peru; 1357, 928, 24027 for Portugal; 1557, 663, 23240 for Ecuador; and 2531, 144, 18811 for Saudi Arabia.

2.1. Model estimation

To correctly model the complexities of COVID-19 outcomes and its relationship with meteorological factors, we utilized several panel estimation techniques. First, we assessed the characteristics of the dataset using descriptive statistical tools. We applied data normalization technique following the procedure presented in Sarkodie et al. (2020) to correct negative data inputs without losing the structural attributes of the data.

Second, we examined potential cross-section dependence in panel data. Due to global common shocks (Eberhardt and Teal, 2011) such as, inter alia, pandemics like COVID-19, and climate change, panel data usually suffer from correlation across countries. Hence, ignoring this challenge in model estimation affects statistical inferences. Thus, we controlled for cross-section dependence following the procedure presented in Pesaran (2004).

Third, assessing the stationarity properties of panel dataset is useful to avoid spurious statistical interpretations. We utilized the estimation procedure expounded in Pesaran (2007) to investigate the stationarity of the data using CIPS and CADF panel unit root techniques.

Next, we examined the panel data for potential heterogeneity and applied the panel-based causality test for the heterogeneous panel. Like cross-section dependence, panel data also suffer from heteroskedasticity due to different characteristics across countries. Hence, we controlled for heterogeneity using the modified Wald (MWALD) test for groupwise heteroskedasticity in the fixed-effects regression model (Greene, 2000). Subsequently, we investigated the causation between COVID-19 outcomes and meteorological factors using panel heterogeneous causality. This panel estimation procedure is essential to test the null hypothesis that meteorological factors do not predict COVID-19 health outcomes. The model specification for the null hypothesis is expressed as (Dumitrescu and Hurlin, 2012):

$$lny_{i,t} = \propto_i + \sum_{k=1}^{K} \gamma_i^{(k)} lny_{i,t-k} + \sum_{k=1}^{K} \delta_i^{(k)} lnx_{i,t-k} + \varepsilon_{i,t} \, for \, i = 1, …, N \, and \, t = 1, …, T$$

(1)

where $\propto_i$ is the country-specific fixed-effects, y denotes COVID-19 outcomes in a stationary form, x represents meteorological factors in a stationary form, i denotes the top 20 COVID-19 cases, t is the time in days from January 22, 2020, to April 27, 2020, K is the lag order for the 20 countries, $\gamma_i^{(k)}$ and $\delta_i^{(k)}$ are the autoregressive (AR) parameter and

Table 1
Descriptive features of Meteorological factors and COVID-19.

Variable	Obs	Mean	Std. Dev.	Min	Max
T2MDEW	1940	3.633093	10.54526	−45.14	23.94
T2M_MAX	1940	13.78615	12.22976	−38.31	43.09
T2M_MIN	1940	4.124778	11.41262	−44.25	27.52
T2M	1940	8.742072	11.5016	−41.79	35.51
WS2M	1940	2.436335	1.809192	0	10.74
PRECTOT	1940	2.527541	5.947759	0	95.97
RH2M	1940	73.68099	21.33304	0	100
PS	1940	92.92131	11.54414	0	103.56
RECOVERED	1940	7597.798	19512.98	0	120832
DEATHS	1940	1903.183	5584.873	0	56259
CONFIRMED	1940	29000.31	84310.74	0	988197

Legend: T2MDEW - Dew/Frost Point at 2 Meters (°C), T2M_MAX - Maximum Temperature at 2 Meters (°C), T2M_MIN - Minimum Temperature at 2 Meters (°C), T2M - Temperature at 2 Meters (°C), WS2M - Wind Speed at 2 Meters (m/s), PRECTOT – Precipitation (mm day^{-1}), RH2M - Relative Humidity at 2 Meters (%), PS - Surface Pressure (kPa), RECOVERED - Recovered Cases of COVID-19 recorded (persons), DEATHS – Deaths of COVID-19 recorded (persons) and CONFIRMED - Confirmed Cases of COVID-19 recorded (persons).

slope coefficient of the regression that differs across the 20 countries. The model is based on a log-log estimation procedure, hence, coefficients are interpreted as elasticities.

In line with a previous study on COVID-19 prediction in China, the spread of SARS-CoV-2 is affected by heterogeneous effects across countries (Sarkodie and Owusu, 2020b). Thus, we used panel biased-correction and heterogeneous panel dynamic techniques to control for panel heterogeneity. For brevity, the generic form of the estimation technique can be expressed as:

$$lny_{i,t} = \delta * lnx_{i,t} + \varepsilon_{i,t} \, for \, i = 1, …, N \, and \, t = 1, …, T$$

(2)

where ln denotes logarithmic transformation, $y_{i,t}$ represents confirmed cases, deaths and recovery cases, δ is the estimated slope coefficient, $x_{i,t}$ denotes the individual meteorological factors and $\varepsilon_{i,t}$ is the panel error term permitted to be heteroskedastic.

3. Results

The descriptive statistical features of the data series are presented in Table 1. From 1940 observations across 20 countries, we detect an average dew/frost point of 3.63°C at 2 m but a minimum frost point of −45.14°C is observed in Russia while a maximum dew point of 23.94°C is observed in Brazil. An average temperature of 8.74°C is observed across countries, however, the minimum temperature of −41.79°C is detected in Russia while the maximum temperature of 35.51°C is observed in India. Contrary to the mean minimum temperature of 4.12°C observed, we also find the minimum of minimum temperature in Russia (−44.25°C) and maximum of minimum temperature in India (27.52°C). The mean maximum temperature is 13.79°C, the minimum of the maximum temperature of −38.31°C is observed in Russia whereas the maximum of maximum temperature occurs in India (43.09°C). The average wind speed observed in the sampled countries is approximately 2.44 m/s at 2 m while a maximum wind speed of 10.74 m/s at 2 m can be observed in the Netherlands. The average precipitation of 2.53 mm day-1 is observed across countries while maximum precipitation of 95.97 mm day-1 occurs in Peru. The average relative humidity is 73.68% at 2 m while a maximum of 100% relative humidity is observed in Russia. While the mean surface pressure is 92.92 kPa across 20 countries, the maximum surface pressure of 103.56 kPa occurs in the Netherlands. As of April 27, the total confirmed cases presented in Fig. 1 for the top 20 countries totalled 2,627,713. The US is so far the epicentre of COVID-19 with 988,197 confirmed cases and 56,259 deaths. However, Spain, the second country after the US with a higher number of confirmed cases, has the highest global recovery rate of about 120,832.
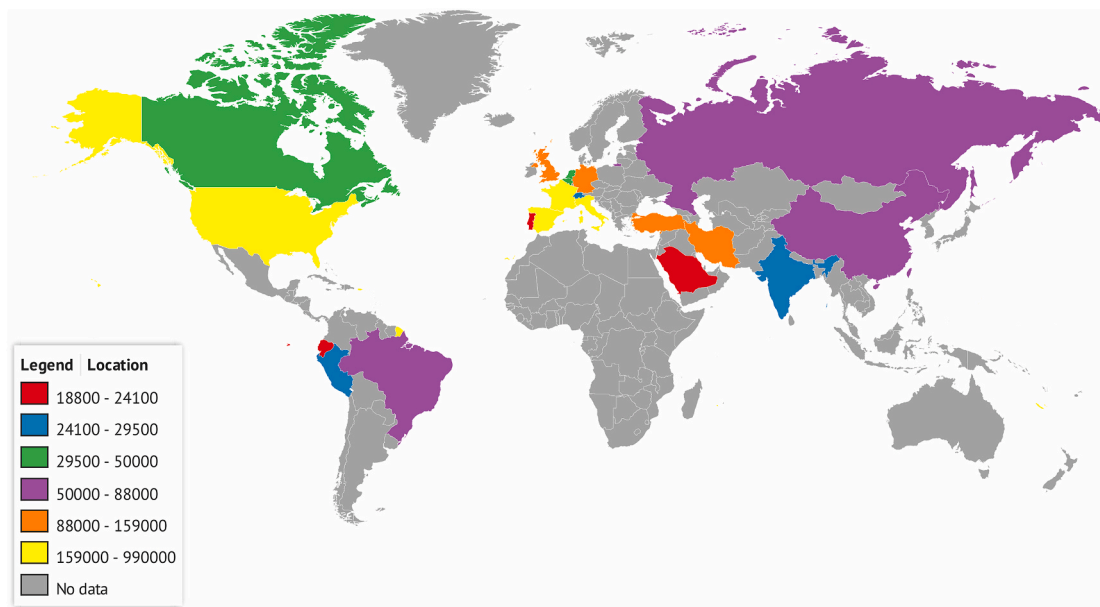
Fig. 1. Confirmed cases of COVID-19 in top 20 countries.

Table 2

Testing Panel Unit Root of Meteorological factors and COVID-19.

Variable	CD	CIPS	ΔCIPS	CADF	ΔCADF
T2MDEW	25.29***	−3.933***	−5.851***	−10.932***	−20.102***
T2M_MAX	55.27***	−4.411***	−6.190***	−13.493***	−21.438***
T2M_MIN	32.65***	−3.881***	−6.077***	−10.383***	−20.475***
T2M	53.64***	−3.970***	−6.029***	−12.361***	−20.883***
WS2M	17.52***	−5.650***	−6.190***	−17.256***	−21.673***
PRECTOT	3.77***	−5.764***	−6.190***	−18.813***	−21.673***
RH2M	57.85***	−4.435***	−6.190***	−11.808***	−21.673***
PS	135.05***	−3.357***	−5.681***	−8.778***	−18.628***
RECOVERED	104.38***	−0.845	−4.081***	5.774	−12.073***
DEATHS	125.79***	−0.892	−2.169**	5.506	−6.537***
CONFIRMED	120.52***	−1.112	−2.866***	3.857	−5.897***

Notes: **, *** signify the rejection of the null hypothesis of cross-section independence for the CD test and stationarity for CIPS and CADF tests at *p-value < 0.05* and *p-value < 0.01*; Δ is the first-difference operator. **Legend:** T2MDEW - Dew/Frost Point at 2 Meters (°C), T2M_MAX - Maximum Temperature at 2 Meters (°C), T2M_MIN - Minimum Temperature at 2 Meters (°C), T2M - Temperature at 2 Meters (°C), WS2M - Wind Speed at 2 Meters (m/s), PRECTOT – Precipitation (mm day^{-1}), RH2M - Relative Humidity at 2 Meters (%), PS - Surface Pressure (kPa), RECOVERED - Recovered Cases of COVID-19 recorded (persons), DEATHS – Deaths of COVID-19 recorded (persons) and CONFIRMED - Confirmed Cases of COVID-19 recorded (persons).

3.1. Estimation results

Panel data models often suffer from cross-section dependence (CD) and heterogeneity, which affect model specification and statistical inferences. Thus, we began the panel model estimation by testing for possible evidence of cross-section dependence and stationarity of meteorological factors and COVID-19. Using the panel cross-section dependence test expounded in Pesaran (2004), we investigated each data series under the null hypothesis of cross-section independence. Evidence from the CD test in Table 2 reveals a rejection of the null hypothesis at *p-value < 0.01*, thus, confirming the presence of cross-section dependence. A validation of cross-section dependence declares the application of first-generational unit root tests as null and void. Meaning that testing for panel unit root requires second-generational panel unit root tests outlined in Le and Sarkodie (2020). Testing for panel unit root is essential to avoid possible spurious and misleading statistical inferences. Using the second-generational panel-based unit root tests namely CIPS (Pesaran, 2007) and CADF (Pesaran et al., 2003), we estimated the stationarity of the data series. Aside from the importance of CIPS and CADF in controlling for cross-section dependence, the two tests are useful in heterogeneous panel — a challenge in this study. The results from CIPS and CADF panel unit root tests show that the null hypothesis of nonstationarity is strongly rejected at level (*p-value < 0.01*) in all meteorological factors. Meaning that while meteorological factors are stationary at level, variables of COVID-19 are differenced-stationary.

To select the required estimation technique for the proposed model, we proceeded to examine panel heterogeneity and panel causality presented in Table 3. Using MWALD test for groupwise heteroskedasticity in the fixed-effects regression model, we investigated panel heterogeneity based on the null hypothesis of homogeneity. The estimated MWALD results reject the null hypothesis at *p-value < 0.01*, thus, violating the normality assumption and confirming the presence of heterogeneity in the panel. Based on the estimation procedure presented in Dumitrescu and Hurlin (2012), we examined the direction of causation between meteorological factors and COVID-19 outcomes using Granger causality test for panel with heterogenous slope. The results in Table 3 reveal that the null hypothesis that meteorological factors do not Granger cause COVID-19 outcomes is rejected at 1% significance level. Thus, very strong causation exists from meteorological factors to COVID-19 outcomes. Meaning that dew/frost point, temperature, wind speed, relative humidity, precipitation and surface pressure are good predictor of

Table 3
Panel Heterogenous Causality of Meteorological factors and COVID-19.

Variable	DEATHS	CONFIRMED	RECOVERED
T2MDEW	14.3938***	14.5267***	5.1512***
	(Heterogenous)	(Heterogenous)	(Heterogenous)
T2M_MAX	11.6935***	8.1862***	3.0118***
	(Heterogenous)	(Heterogenous)	(Heterogenous)
T2M_MIN	19.0729***	17.3226***	5.3330***
	(Heterogenous)	(Heterogenous)	(Heterogenous)
T2M	13.4777***	10.4969***	1.5708***
	(Heterogenous)	(Heterogenous)	(Heterogenous)
WS2M	2.2461**	5.6359***	4.5602***
	(Heterogenous)	(Heterogenous)	(Heterogenous)
PRECTOT	6.8980***	6.5937***	5.1015****
	(Heterogenous)	(Heterogenous)	(Heterogenous)
RH2M	22.1531***	25.0581***	13.3743***
	(Heterogenous)	(Heterogenous)	(Heterogenous)
PS	17.5137***	23.1377****	4.7666***
	(Heterogenous)	(Heterogenous)	(Heterogenous)
CONFIRMED	645.5828***	–	117.6112***
	(Heterogenous)		(Heterogenous)

Notes: (Heterogenous) represents a rejection of the null hypothesis of homogeneity at *p-value < 0.01* using the modified Wald test for groupwise heteroskedasticity in the fixed effect regression model. **,*** denote rejection of the null hypothesis that *X* does not Granger-cause *Y* in at least one country. **Legend:** T2MDEW - Dew/Frost Point at 2 Meters ($^{\circ}$C), T2M_MAX - Maximum Temperature at 2 Meters ($^{\circ}$C), T2M_MIN - Minimum Temperature at 2 Meters ($^{\circ}$C), T2M - Temperature at 2 Meters ($^{\circ}$C), WS2M - Wind Speed at 2 Meters (m/s), PRECTOT – Precipitation (mm day^{-1}), RH2M - Relative Humidity at 2 Meters (%), PS - Surface Pressure (kPa), RECOVERED - Recovered Cases of COVID-19 recorded (persons), DEATHS – Deaths of COVID-19 recorded (persons) and CONFIRMED - Confirmed Cases of COVID-19 recorded (persons).

Table 4
Nexus between COVID-19 and Meteorological factors.

Variable	CONFIRMED	DEATHS	RECOVERED
T2MDEW	10.9987***	11.1592***	−0.1010***
[Std. Err.]	[0.4350]	[0.4262]	[0.0029]
(Prob > chi^2)	(0.0000)***	(0.0000)***	(0.0000)***
R-squared	0.37	0.41	0.76
T2M	−0.1302 ***	−0.1086***	10.1719***
[Std. Err.]	[0.0029]	[0.0024]	[0.3999]
(Prob > chi^2)	(0.0000)***	(0.0000)***	(0.0000)***
R-squared	0.63	0.67	0.59
T2M_MAX	−0.1252***	−0.1051***	9.6982***
[Std. Err.]	[0.0028]	[0.0024]	[0.3566]
(Prob > chi^2)	(0.0000)***	(0.0000)***	(0.0000)***
R-squared	0.63	0.66	0.59
T2M_MIN	9.6446***	10.0823***	−0.1021***
[Std. Err.]	[0.3978]	[0.3923]	[0.0031]
(Prob > chi^2)	(0.0000)***	(0.0000)***	(0.0000)***
R-squared	0.37	0.41	0.74
WS2M	2.3656***	2.3809***	−0.16204***
[Std. Err.]	[0.0874]	[0.0796]	[0.0064]
(Prob > chi^2)	(0.0000)***	(0.0000)***	(0.0000)***
R-squared	0.36	0.46	0.57
PRECTOT	1.0005***	0.8641***	−0.0710***
[Std. Err.]	[0.0311]	[0.0296]	[0.0020]
(Prob > chi^2)	(0.0000)***	(0.0000)***	(0.0000)***
R-squared	0.53	0.55	0.04
RH2M	−0.0879***	−0.0752***	4.1816***
[Std. Err.]	[0.0020]	[0.0020]	[0.3838]
(Prob > chi^2)	(0.0000)***	(0.0000)***	(0.0000)***
R-squared	0.62	0.63	0.18
PS	62.3719***	48.2287***	−0.0712***
[Std. Err.]	[0 2.6108]	[0 2.4816]	[0.0021]
(Prob > chi^2)	(0.0000)***	(0.0000)***	(0.0000)***
R-squared	0.33	0.35	0.71

Notes: **, *** signify the rejection of the null hypothesis of stationarity at *p-value < 0.05* and *p-value < 0.01*; Δ is the first-difference operator. **Legend:** T2MDEW - Dew/Frost Point at 2 Meters ($^{\circ}$C), T2M_MAX - Maximum Temperature at 2 Meters ($^{\circ}$C), T2M_MIN - Minimum Temperature at 2 Meters ($^{\circ}$C), T2M - Temperature at 2 Meters ($^{\circ}$C), WS2M - Wind Speed at 2 Meters (m/s), PRECTOT – Precipitation (mm day^{-1}), RH2M - Relative Humidity at 2 Meters (%), PS - Surface Pressure (kPa), RECOVERED - Recovered Cases of COVID-19 recorded (persons), DEATHS – Deaths of COVID-19 recorded (persons) and CONFIRMED - Confirmed Cases of COVID-19 recorded (persons).

confirmed COVID-19 cases, deaths and recovery cases. Besides, we find strong evidence of causality from confirmed cases to deaths and recovery cases.

After confirming the causation between meteorological factors and COVID-19 outcomes, we examined the magnitude and individual effect of dew/frost point, temperature, wind speed, relative humidity, precipitation and surface pressure on confirmed cases, deaths and recovery cases. To control for heteroskedasticity, we adopted linear regression with heterogeneous panel-corrected standard errors. We examined the individual effect of meteorological factors on COVID-19 outcomes presented in Table 4. The estimated coefficient on T2MDEW is positive for confirmed cases and deaths but negative for recovery cases. Meaning that a percentage increase in dew/frost point intensifies confirmed cases and deaths by ~11% (*p-value < 0.01*) but declines recovery cases by 0.10% (*p-value < 0.01*). The coefficient on T2M is negative for confirmed cases and death but positive for recovery cases. We observe that a percentage increase in temperature declines confirmed cases and deaths by 0.13% (*p-value < 0.01*) and ~0.11% (*p-value < 0.01*), respectively but improves recovery cases by 10% (*p-value < 0.01*). To ascertain the degree of temperature (cold or warm) that affects COVID-19 outcomes, we investigated disaggregate (minimum and maximum) effects of temperature. The coefficient on T2M_MAX is negative for confirmed cases and death but positive for recovery cases. Thus, increasing maximum temperature by 1% declines confirmed cases by 0.13% (*p-value < 0.01*) and deaths by 0.11% (*p-value < 0.01*) but increases recovery cases by ~10% (*p-value < 0.01*). In contrast, a percentage increase in minimum temperature upsurges both confirmed cases and deaths by ~10% (*p-value < 0.01*) but declines recovery cases by 0.10% (*p-value < 0.01*). The coefficient on RH2M is negative and statistically significant for confirmed cases and death while the coefficient is positive for recovery cases. In the same way, increasing relative humidity by 1% declines confirmed cases and deaths by ~0.08% (*p-value < 0.01*) but intensifies recovery cases by ~4% (*p-value < 0.01*).

While the coefficient on WS2M is positive for confirmed cases and death, we observe a negative coefficient for recovery cases. The empirical evidence shows that a percentage increase in wind speed

increase confirmed cases and deaths by almost 2% (*p-value < 0.01*) while recovery cases decline by 0.16% (*p-value < 0.01*). The corresponding coefficient on PRECTOT and PS is positive and statistically significant at 1% level for confirmed cases and deaths but negative for recovery cases. An increase in precipitation by 1% declines recovery cases 0.07% and increases confirmed cases and deaths by 1% and 0.86%, respectively. A percentage increase in surface pressure escalates confirmed cases and deaths by 62% and 48% while it declines recovery cases by 0.07%.

After the model estimation, we validated the heterogeneous parameters using the kernel density estimation for heterogeneous panel depicted in Fig. 2. Based on the split-panel jackknife method, we validate the usefulness of investigating the individual effects of meteorological factors on COVID-19 outcomes. This means that a model specification that estimates all series in one equation will produce erroneous results. Evidence from Fig. 2 shows that all data series have different distributions within the 95% confidence band, hence, validating the heterogeneous panel-based estimation models.

4. Discussion

Our study for the first time examined the impact of meteorological factors on COVID-19 outcomes based on novel heterogeneous panel estimation techniques. The empirical results showed that high-temperature declines confirmed cases and deaths of COVID-19 whereas cold temperatures heighten confirmed cases which result in deaths. High temperature is reported to slow the spread of COVID-19,
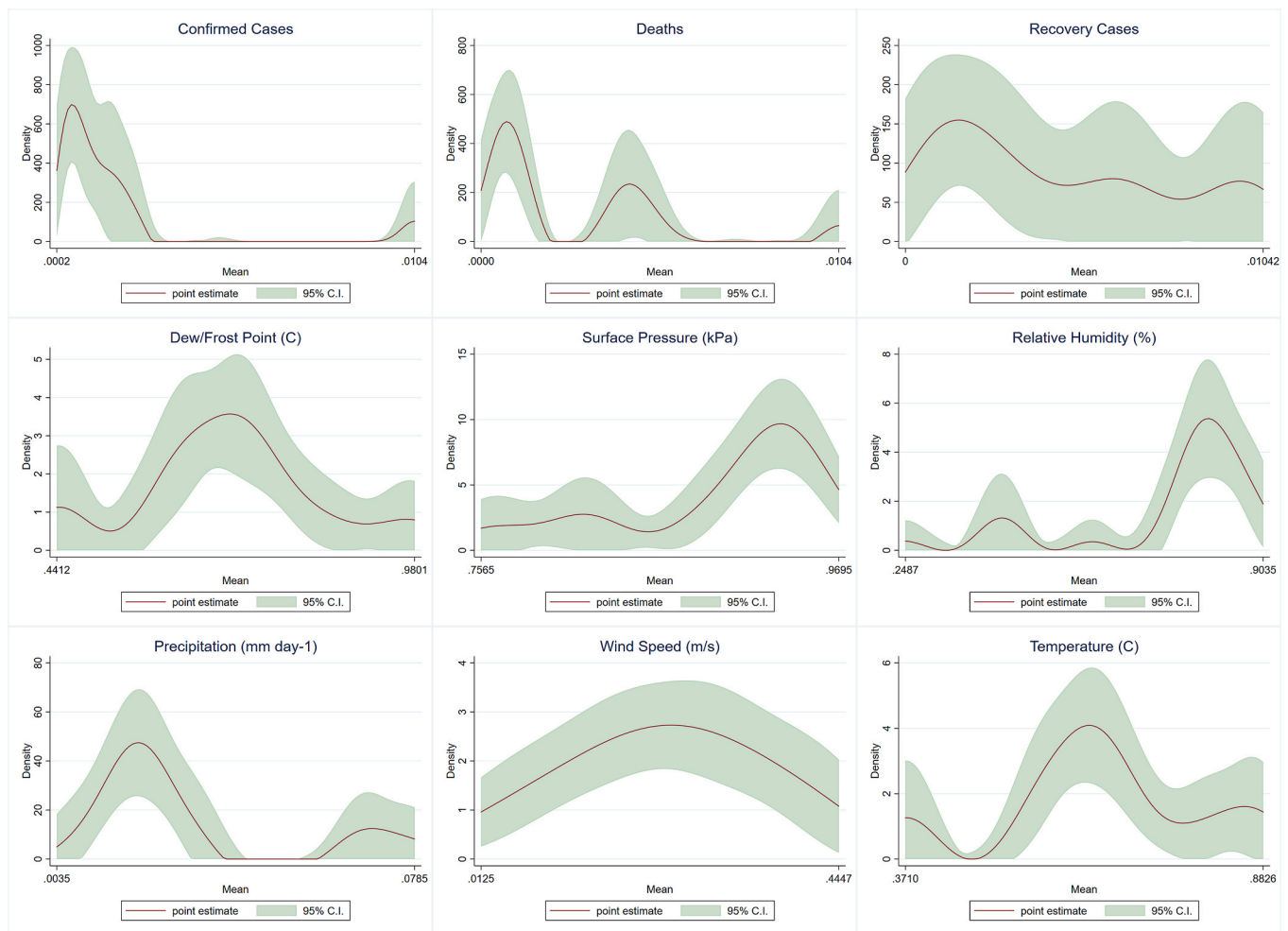
Fig. 2. Heterogeneous Panel Dynamics of COVID-19 and Meteorological factors.

hence, serves as a mitigating effect against the survival and transmission of the virus. On the contrary, cold temperature becomes a haven for coronaviruses and speeds up their survival and transmission. Coronaviruses are reported to remain active, stable and viable in low temperatures, hence, facilitate its transmission and increase the incidence of reported cases (Chan et al., 2011). A similar study in 122 Chinese cities found confirmed cases to decline by 4.9% when temperature increases by 1°C (Xie and Zhu, 2020). It is reported that the persistence of coronaviruses on nonliving objects last longer in low temperatures whereas high temperatures decline the persistence of the viruses (Casanova et al., 2010). Several studies report a rapid decline of stability and viability of coronaviruses such as the Middle East respiratory syndrome coronavirus (MERS-CoV), severe acute respiratory syndrome coronavirus (SAR-S-CoV) at high temperatures (Chan et al., 2011; Van Doremalen et al., 2013).

In contrast, we found a strong relationship and causation between moisture-based meteorological factors and confirmed cases. Dew/frost point and precipitation act as confounders for COVID-19-temperature nexus by reducing high temperatures to low levels and converting dry environment to moist and cold conditions that are conducive for the survival and transmission of the virus. Consistent with Sizun et al. (2000), it was reported that human coronaviruses survive in moist suspension for several days but few hours for a dry environment. This possibly explains the human-to-human COVID-19 transmission from inanimate surfaces through hand contamination (Sizun et al., 2000). Skin contamination of coronaviruses are possible and immediate from non-absorptive surfaces in a moist environment (can survive for 10 h)

compared to dry surfaces (can survive for 2 h) (Brady et al., 1990; Sizun et al., 2000).

We found a strong relationship between relative humidity and incidence of COVID-19, consistent with extant literature on coronaviruses (Casanova et al., 2010; Chan et al., 2011; Van Doremalen et al., 2013). Relative humidity renders coronaviruses inactive, especially on inanimate objects. Higher relative humidity is reported to decrease the viability and persistence of the viruses compared to lower relative humidity. Coronaviruses are reported to survive in low relative humidity, hence, prolong its viability and stability on contaminated surfaces. Thus, the contamination of coronaviruses can be retained for 14 days in an environment with low relative humidity and low temperature (Chan et al., 2011).

Both wind speed and surface pressure are found to escalate confirmed cases of SARS-CoV-2 across countries. If the airborne factor of coronaviruses holds, then, both wind speed and surface pressure intensities fast-track the spread of the virus, by accelerating the mode of travel from one location to another. This perhaps explains why the use of nose masks in countries like Hong Kong, Vietnam, Taiwan, Thailand, Slovakia and the Czech Republic slowed the spread of the virus (Servick, 2020; Ting, 2020). Regardless, wind speed and surface pressure intensities carry droplets with the virus to different destination. This transmission cycle might explain cases of COVID-19 without human-to-human transmission and community spread through skin contact.

Our results confirmed a causal relationship running from the incidence of COVID-19 cases to deaths. In conjunction, while high
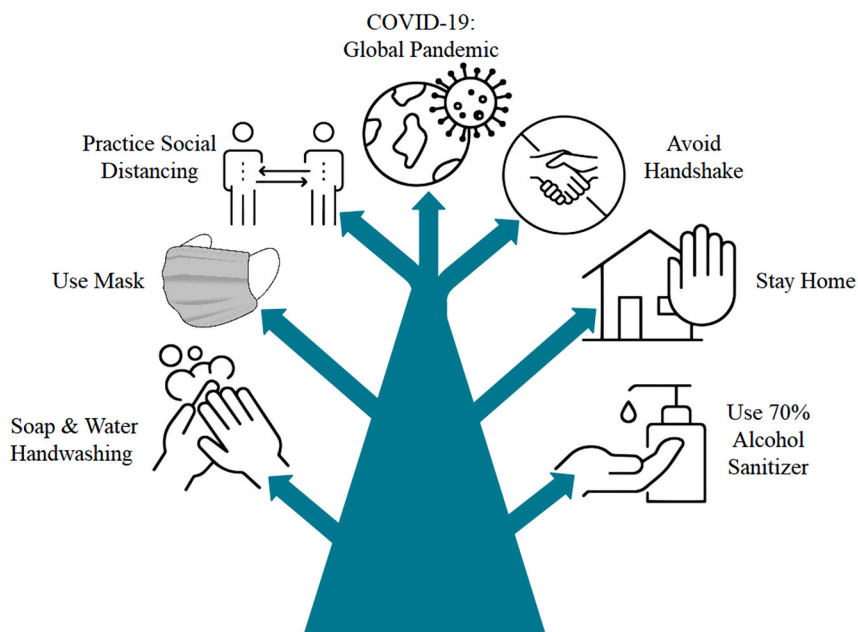
Fig. 3. Policy implications of the nexus between COVID-19 and Meteorological factors.

temperature and high humidity decline COVID-19 deaths and surge recovery rates, other meteorological factors such as minimum temperature, wind speed, surface pressure, dew/frost point and precipitation increase the rate of deaths from COVID-19 and negate the rate of recovery. Apart from the impact of meteorological conditions on the survival of viruses, there are cases of reported effect of weather conditions on the human immune system. For example, cold regions with limited exposure to sunlight are reported to have many cases of Vitamin D deficiency compared to tropical regions (Cannell et al., 2006). Low levels or lack of Vitamin D affects the anti-microbial peptide system responsible for the regulation of human immune response (Fuhrmann, 2010). Exposure to extremely dry and cold weather conditions is reported to modify the human immune response, hence, the host becomes susceptible to pathogen-causing infections (Fisman, 2007). This perhaps explains why the majority of COVID-19 attributable deaths reported has potential risk factors or underlying health conditions (Covid et al., 2020). It is reported that Vitamin D plays a critical role in reducing the risk of COVID-19 infections and death rates (Grant et al., 2020). The mechanism of Vitamin D includes lowering COVID-19 viral replication levels, suppressing pro-inflammatory and raising the anti-inflammatory concentration of cytokines by inducing defensins and cathelicidins (Grant et al., 2020; Herr et al., 2007; Laaksi, 2012).

The empirical results of the study have policy implications for preventing the incidence of COVID-19 (Fig. 3). The practice of social distancing (ID 1) measures including staying home (ID 2) and preventive measures such as avoiding handshake (ID 3), using face mask (ID 4), handwashing with soap and running water (ID 5) and applying 70% alcohol-based sanitizer (ID 6) — will help reduce the spread of COVID-19. The safety measures in Fig. 3 mitigate the effect of meteorological factors in facilitating COVID-19 viral transmission through contact transmission (ID 1–3, 5–6), droplet transmission (ID 1, 3–6), and airborne transmission (ID 4).

5. Conclusion

As a contribution to the global debate on the novel coronavirus (COVID-19), we examined the nexus between meteorological factors and COVID-19 outcomes in the top 20 countries with confirmed cases. Using daily data from 01/22/2020 to 04/27/2020, we utilized a battery of panel estimation techniques to control the complexities of SARS-CoV-

2. We found that, first, using disaggregate temperature rather than average temperature provides more insight into understanding the temperature-SARS-CoV-2 nexus. Second, due to potential heterogeneity, using all meteorological factors in a single model lead to erroneous estimates, hence, producing spurious inferences especially in panel data. Thus, controlling for individual-specific effects of meteorological factors on COVID-19 is worthwhile. Our results confirmed a strong causal relationship between meteorological factors and COVID-19 outcomes. While high temperature and high relative humidity were found to reduce incidence cases, low temperature, wind speed, surface pressure, dew/frost point and precipitation were found to facilitate the survival and transmission of COVID-19, hence, increasing confirmed cases, deaths and reducing recovery rates. We propose laboratory examination of the effect of wind speed, surface pressure, dew/frost point and precipitation on coronaviruses. Future research should aim at assessing the socio-economic impact on the spread and containment of COVID-19 outcomes. To further understand the dynamics of the pandemic, the effect of other confounding factors like medical conditions and preventive policies (inter alia, social-distancing, circulation of personal protective equipment, and restrictive testing) should be examined across countries.

Author contribution

Samuel Asumadu Sarkodie: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Software, Validation; Visualization, Writing - review & editing. Phebe Asantewaa Owusu: Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

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