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Asymmetric impact of temperature on COVID-19 spread in India: Evidence from quantile-on-quantile regression approach

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ABSTRACT

The emergence of new coronavirus (SARS-CoV-2) has become a significant public health issue worldwide. Some researchers have identified a positive link between temperature and COVID-19 cases. However, no detailed research has highlighted the impact of temperature on COVID-19 spread in India. This study aims to fill this research gap by investigating the impact of temperature on COVID-19 spread in the five most affected Indian states. Quantile-on-Quantile regression (QQR) approach is employed to examine in what manner the quantiles of temperature influence the quantiles of COVID-19 cases. Empirical results confirm an asymmetric and heterogeneous impact of temperature on COVID-19 spread across lower and higher quantiles of both variables. The results indicate a significant positive impact of temperature on COVID-19 spread in the three Indian states (Maharashtra, Andhra Pradesh, and Karnataka), predominantly in both low and high quantiles. Whereas, the other two states (Tamil Nadu and Uttar Pradesh) exhibit a mixed trend, as the lower quantiles in both states have a negative effect. However, this negative effect becomes weak at middle and higher quantiles. These research findings offer valuable policy recommendations.

1. Introduction

On 30 January, 2020, the WHO declared the new coronavirus (2019-nCoV)-infected pneumonia epidemic a Public Health Emergency of International Concern (Ali et al., 2020). It is an encapsulated single-stranded RNA virus that causes mild symptoms (related to the common cold) to more acute respiratory, intestinal hepatic, and

neurological problems (Iqbal et al., 2021). According to available information, the major mode of transmission for COVID-19 virus is by respiratory droplets and direct contact (Elavarasan et al., 2021b). COVID-19 can cause symptoms such as fever, breathing difficulties, coughing (usually dry), and invading infections on both lungs of individuals (Ahmad et al., 2020; Khan et al., 2021). Globally, the number of instances of COVID-19 is increasing, resulting in severe consequences ranging from macroeconomic to individual social protection,

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particularly in low-income nations (Yu et al., 2021). The pandemic has spread to 216 countries with 211 M confirmed cases and 4.42 M re-

Nomenclature	
<i>Abbreviations</i>	
AIDS	Acquired Immunodeficiency Syndrome
COVID-19	Novel Coronavirus disease 2019
MERS-CoV	The Middle East Respiratory Syndrome Coronavirus
SARS-CoV	Severe Acute Respiratory Syndrome Coronavirus
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus-2
<i>Methods</i>	
ADF	Augmented Dickey-Fuller test
JB	Jarque-Bera test
QQR	Quantile-on-Quantile Regression
ZA	Zivot-Andrews test

ported deaths (Worldometers, 2021). COVID-19 has not been entirely eliminated in developed and underdeveloped countries (Ahmad et al., 2021a). Even some territories are experiencing an increasing tendency (Shah et al., 2020) mainly because disease-resistant medicines and vaccines are unavailable (Ahmad et al., 2020; Irfan et al., 2021e).

Being neighboring with China, India, with a massive population of 1.35×10^9 is also striving against novel coronavirus. Until 02 March 2020, India only reported three COVID-19 cases (Singhal, 2020). However, the total number of confirmed COVID-19 cases increased to thousands in the next month (Mandal and Mandal 2020), with Maharashtra state having the highest number of cases, followed by Tamil Nadu, Andhra Pradesh, Karnataka, and Uttar Pradesh. At the moment, the number of COVID-19 cases are rising rapidly, and the situation is deteriorating. The government data revealed that the COVID-19 patients increased to 32.3 M in India, with 434,074 fatalities (COVID-19 India, 2021). Fig. 1 shows the confirmed COVID-19 cases in the top five Indian states affected by the pandemic.

India's current challenge is the battle against the pandemic, which has recently attracted worldwide attention. India is a developing nation (Elavarasan et al., 2021a; Irfan et al., 2019a, 2019b), with inadequate resources and healthcare infrastructure in comparison to rich economies. (Ahmad et al., 2021c; Hao et al., 2020; Irfan et al., 2021c; Li et al., 2021). The main economic operations of the nation have been significantly affected owing to the coronavirus epidemic. As a result, industrial manufacturing facilities have ceased operations, with little traffic

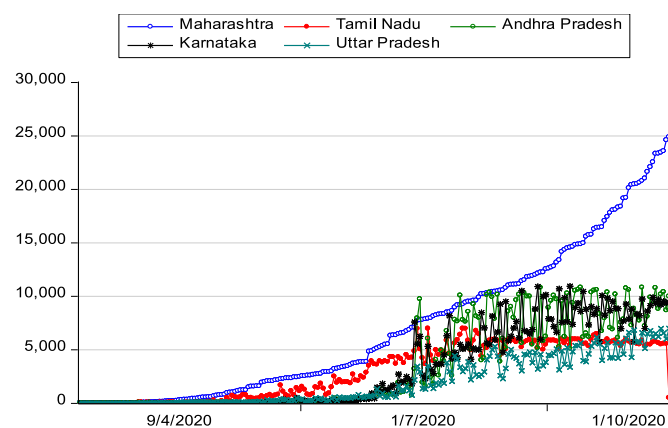


Fig. 1. Confirmed COVID-19 cases in the five Indian states. Notes: Y-axis depicts confirmed COVID-19 cases and X-axis represents the time period.

movement, causing a significant decline in air pollution (Muhammad et al., 2020). Razaq et al. (2020) reported that the ozone depletion risk has substantially reduced due to a drop in carbon emissions level, which, in turn, influences the daily temperature. Though public health has notably improved in underdeveloped economies (Papadimitriou, 2004), the threat of pandemics would continue due to ecological elements (Bontempi, 2020).

Previous studies were mainly centered on scrutinizing the environmental impacts of COVID-19. Among them, the first group of researchers focused on the epidemiology of COVID-19 (Collivignarelli et al., 2020; McIntosh, 2020) and the interaction of environmental and climatic factors with COVID-19 (Irfan et al., 2021a, 2021d). The second group of researchers investigated the influence of psychological factors on COVID-19 (León-Zarceño et al., 2021; Sherman et al., 2021). The third group of researchers focused on the situation review of disease profiles in order to devise preventive and control mechanisms (Allam et al., 2020; Gao and Yu, 2020). The fourth group of researchers examined the environmental impacts of COVID-19 (Irfan et al., 2021a, 2021d; Zambrano-Monserrate et al., 2020), whereas the fifth group of researchers examined how people perceive the need to avoid epidemics such as MERS-CoV, SARS-CoV, and COVID-19 (Chughtai and Khan, 2020; Irfan et al., 2021b). Despite previous researchers' long-standing interests, the propensity to scrutinize the linkage between temperature (centigrade °C) and COVID-19 (head count of positive cases) is of increasing concern. Taking this debate into account, the present work is intended to respond to this research gap by conducting a comprehensive research in the top five most affected Indian states. Thus, the primary objective of this paper is to expose the asymmetric impact of temperature on COVID-19 spread.

The rest of the paper is organized as follows. Section 2 provides details about data sources. Section 3 explains the methodology of the study. Research results and discussion are reported in section 4. Finally, the concluding remarks and policy implications are presented in the last section of the paper.

2. Data

This paper draws an association between temperature (centigrade °C) and COVID-19 spread in the five most affected Indian states. The NASA database is used to get daily data of mean temperature (NASA, 2021), whereas the official website of Indian government is used to gather data on COVID-19 cases (COVID-19 India, 2021). Fig. 2 shows the temperature patterns in the five COVID-19 affected Indian states. Each state's capital city is chosen for temperature input since it contains the majority of the population and has superior healthcare services. As a

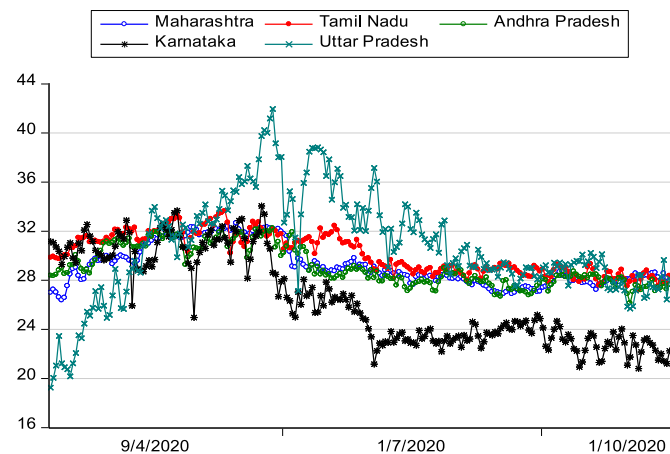


Fig. 2. Temperature patterns in the five COVID-19 affected Indian states. Notes: Y-axis represents temperature (centigrade °C) and X-axis represents the time period.

result, the influx of patients is greatest here in comparison to other cities. Additionally, each major city has an international airport, indicating a significant potential of viral infection. The COVID-19 cases in our selected states are shown in Fig. 3.

3. Methodology

3.1. Data normality and unit root test

Before employing the QQR model, the normality of the data is checked by conducting a unit root test. The purpose of performing the unit root test is to confirm the stationarity of the chosen variables. Table 1 reports the descriptive statistics of both variables. The statistics of the Jarque-Bera (JB) test are significant at 1% significance, implying that there is an asymmetric distribution of temperature and COVID-19 cases in all Indian states under discussion. The results of the Augmented Dickey-Fuller (ADF) test revealed that there is non-stationarity at levels among selected variables. Kim and Choi (2017) stated that if the data have structural break problems, then the ADF test could produce bias and ambiguous results (Shahbaz et al., 2015). To overcome this problem, we performed the Zivot-Andrews (ZA) test to control the single data structural break (Ahmed et al., 2019). The key benefit of performing the ZA test is that it solves the structural break problems in an endogenous manner. Table 1 indicates that both variables are non-stationary at level but become stationary at first difference.

3.2. Quantile-on-Quantile regression (QQR) analysis

The QQR is the advanced form of conventional quantile regression. The method is robust and most suitable to examine the non-linear

distributions of asymmetrical variables that generate robust estimates while assuming the prime distribution of data. The fundamental rationale of utilizing the QQR method is to find out the non-linear behavior between the studied variables (Shahbaz et al., 2018). Shahzad et al. (2020) discussed that the QQR method combines the characteristics of both quantile and non-parametric regression to identify the asymmetrical and spatial properties of the model over time. Sim and Zhou (2015) described that the QQR approach provides more inclusive results as compared to conventional quantile regression. They utilized this approach in the subsequent three stages. Firstly, the impact of a particular temperature quantile on COVID-19 is assessed by linear regression to resolve the dimensionality problem by allocating extra weights in the closest quantiles. Secondly, the conventional quantile regression is used to determine the impact of an indicator. For instance, temperature, on different quantiles of a standard variable such as COVID-19. Finally, the conventional quantile regression is again utilized to investigate the temperature impact on COVID-19 at both quantiles (head and tail) of distribution data.

Keeping in view the advantages of using the QQR method, the present research employs the novel QQR method to scrutinize the asymmetrical impact of temperature on COVID-19 spread. This method is non-parametric model-based quantile regression framework.

$$C19_t = \alpha^\varnothing (Temp_t) + \beta_t^\varnothing \tag{1}$$

Here, $C19_t$ denotes COVID-19 at t period, $Temp_t$ indicates temperature (centigrade °C) at t period, $\alpha^\varnothing (\cdot)$ used as there is no previous information existed on the impact of $Temp$ and $C19$, \varnothing denotes the \varnothing^{th} quantile of the provisional dispersion of $C19$, while β_t^\varnothing denotes the quantile residual period who's provisional \varnothing^{th} quantile has zero value.

The QQR method assists in examining the impact of $Temp$ on $C19$ at different quantiles in the most affected states of India. The method is

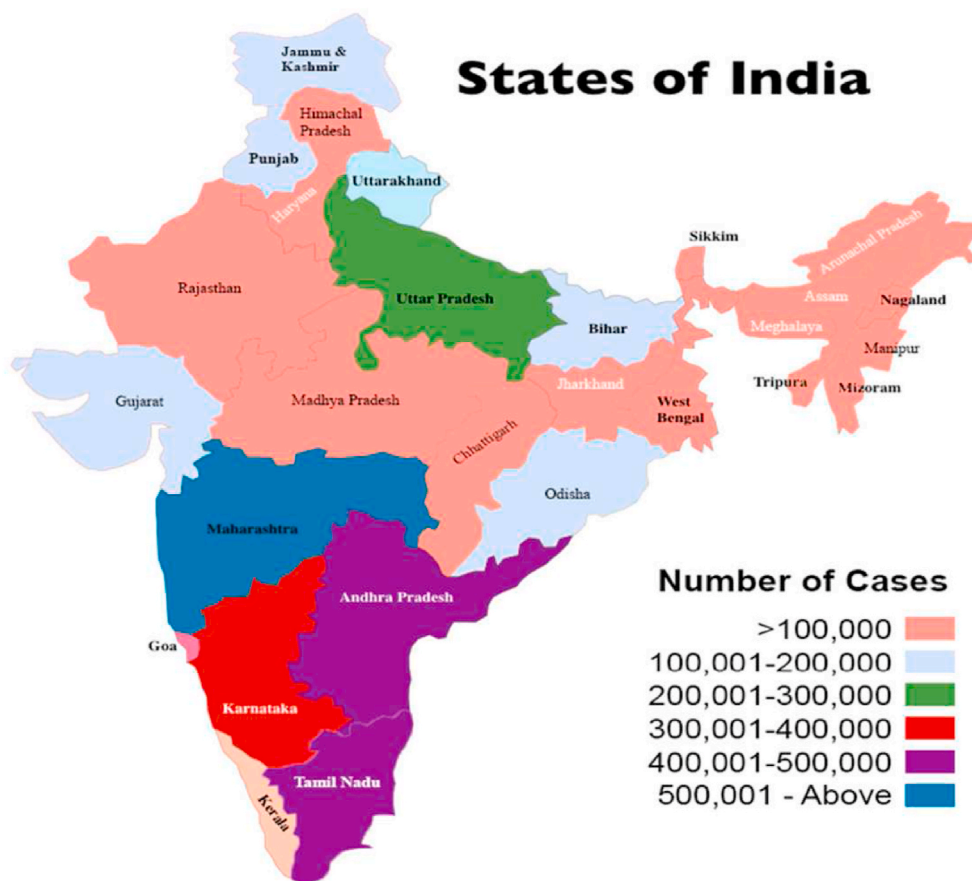


Fig. 3. Map of Indian states with maximum COVID-19 cases.

Table 1
Results of descriptive statistics and unit root.

States	Mean	Min	Max	Std. Dev	J-B stats	ADF (1)	ZA (1)	Breaks
Panel A: Temperature								
Maharashtra	29.89	26.38	32.65	1.625	8.9292***	-9.181***	-9.872***	29-Jun-20
Tamil Nadu	30.98	28.13	33.65	1.340	6.593***	-10.205***	-4.769***	24-Jun-20
Andhra Pradesh	29.83	27.09	32.24	1.491	12.160***	-9.678***	-4.183***	01-Jun-20
Karnataka	28.16	21.17	34.06	3.424	11.436***	-15.272***	-5.651***	24-May-20
Uttar Pradesh	31.86	19.26	41.96	4.811	8.574***	-12.658***	-5.185***	21-May-20
Panel B: COVID-19 cases								
Maharashtra	2904.57	2	24886	3070.149	23.958***	-14.450***	-12.195***	21-Jun-20
Tamil Nadu	1695.64	1	6993	2032.449	29.837***	-10.118***	-10.426***	03-Jun-20
Andhra Pradesh	972.02	1	9999	2198.778	557.321***	-7.327***	-8.068***	06-Jul-20
Karnataka	855.99	1	9464	1563.063	136.390***	-13.600***	-9.632***	8-Jun-20
Uttar Pradesh	589.51	1	7016	887.56	242.973***	-8.824***	-5.144***	29-Jun-20

Notes: Significance level (***p < 0.001, **p < 0.01, *p < 0.05); **Std. Dev:** standard deviation; **J-B stats:** Jarque-Berra Normality Test.

very flexible, as it could evaluate the functional dependence between *Temp* and C19 in the studied regions. The QQR method has a critical elasticity advantage because it considers temperature-COVID-19 dependency in areas that have not been previously acknowledged. Eq. (1) could be extended to seize the impact of *Temp* on C19 by using the Taylor method as follows:

$$\alpha^\varnothing (Temp_i) \approx \alpha^\varnothing (Temp^T) + \alpha^\varnothing (Temp^T) - (Temp_i - Temp^T) \tag{2}$$

Eq. (2) denotes the relationship between the specific quantile of *Temp* (*T*) and specific quantile of C19 (\varnothing) in the instant neighbor of *Temp*^T. Besides, α^\varnothing computes the marginal influence of *Temp* by acquiring the partial differential of $\alpha^\varnothing (Temp^T)$ in relation to the *Temp* of a specific state in five selected states. Eq. (3) signifies the quantile dual indexing criterion, as \varnothing represent C19 and T represent *Temp*, respectively.

$$\gamma^\varnothing (C19_i) \approx \gamma^\varnothing (C19^T) + \gamma^\varnothing (C19^T) (C19_i - C19^T) \tag{3}$$

Here, γ^\varnothing denotes the marginal impact of C19 and it is the partial variation of $\gamma^\varnothing (C19^T)$ in relation to C19. The coefficients of the conventional regression method should be interpreted as α^\varnothing and γ^\varnothing . $\alpha^\varnothing (Temp^T)$ and $\alpha^\varnothing (Temp^T)$ of Eq. (2) could also be signified as:

$$\alpha^\varnothing (Temp_i) \approx \alpha_0(\varnothing, T) + \alpha_1(\varnothing, T) (Temp_i - Temp^T) \tag{4}$$

Here, the functional constraints of $\alpha^\varnothing (Temp^T)$ and $\alpha^\varnothing (Temp^T)$ are denoted by $\alpha_0(\varnothing, T)$ and $\alpha_1(\varnothing, T)$ based on the quantiles of \varnothing and T. To govern the slope coefficients of C19, alike functional constraints can be taken for $\gamma^\varnothing (C19^T)$ and $\gamma^\varnothing (C19^T)$ when the dependent variable is *Temp*.

$$\gamma^\varnothing (C19_i) \approx \gamma_0(\varnothing, T) + \gamma_1(\varnothing, T) (C19_i - C19^T) \tag{5}$$

In this equation, the functional constraints of $\gamma^\varnothing (C19^T)$ and $\gamma^\varnothing (C19^T)$ are denoted by $\gamma_0(\varnothing, T) + \gamma_1(\varnothing, T)$. By replacing Eqs. (3) and (4), we get the following equations.

$$C19_i = \frac{\alpha_0(\varnothing, T) + \alpha_1(\varnothing, T) (Temp_i - Temp^T) + \beta_i^\varnothing}{*} \tag{6}$$

$$Temp_i = \frac{\gamma_0(\varnothing, T) + \gamma_1(\varnothing, T) (C19_i - C19^T) + \beta_i^\varnothing}{*} \tag{7}$$

Here, the provisional conditional of \varnothing^{th} quantile of *Temp* and C19 are presented by (*) sign. The actual relationship between the quantiles of C19 and the quantiles of *Temp* is represented by these equations because the coefficients are double indexed with relation to \varnothing and T, and this relationship is associated with their comparative allocations. In Eq. (8), α_0 and α_1 denotes the estimated coefficients of *Temp*.

$$Min_{\alpha_0, \alpha_1} \sum_{i=1}^n \sigma_{\varnothing[(C19_i - \alpha_0 - \alpha_1 (Temp_i - Temp^T))]} \left[\frac{M_n(C19_i) - \tau}{p} \right] \tag{8}$$

The same minimization question can be extracted for detaining the

impact of C-19 on metropolitan *Temp* in Eq. (9).

$$Min_{\gamma_0, \gamma_1} \sum_{i=1}^n \sigma_{\varnothing[(Temp_i - \gamma_0 - \gamma_1 (C19_i - C19^T))]} \left[\frac{M_n(C19_i) - \tau}{p} \right] \tag{9}$$

Here, the quantile loss function is denoted by $\sigma\varnothing(\cdot)$, whereas the $J(\cdot)$ represents the Gaussian kernel function in both minimization problems to improve the efficiency of estimation. A prime bandwidth is critical to confirm the stability between disparity and estimation bias produced due to the smaller or higher interval of k. In the QQR method, the choice of bandwidth “k” is necessary because it regulates the smoothness of estimated coefficients. According to the findings of former studies, a 5% (h = 0.05) density bandwidth feature is designated for the prime criterion of the QQR method (Arain et al., 2020).

The QQR is non-parametric in nature and only provides the direction and intensity of the relationship. The significance and autoregressive structure are also not considered in this approach. However, it is a novel approach that has been commonly used in recent empirical literature to visualize complex relationships across the grid of diverse quantiles. It produced 19*19 matrices of relationship, which are drawn on three-dimensional (3-D) graphs. These visuals help to unveil the diverse relationship in a comprehensive way. For instance, Razaq et al. (2020) applied the same non-parametric approach on log return data to draw asymmetric linkages between COVID-19 and air quality. Recently, Shahzad et al. (2020) examined the empirical link between metrological indicators and COVID-19 spread in China using the QQR approach. Sinha et al. (2020) also used a similar non-parametric approach (QQR) to draw the linkages between technological progression and ambient air pollution. In another study, Chang et al. (2020) examined the impact of oil prices on sectoral stock indices using the QQR approach. Shahbaz et al. (2018) scrutinized the inter-linkages between energy consumption and economic growth in the top ten energy-consuming countries using the QQR approach.

4. Results and discussion

4.1. Descriptive statistics and correlation analysis

Each series’ data is changed in log return, including 221 observations from 09 April to 15 November 2020. It is also pertinent to mention that the log-return of both variables helps to integrate the daily change in both series and adjusted lag effect. Descriptive statistics and unit root test findings for daily temperature and COVID-19 in the studied states are reported in Table 1. It is evident from Table 1 that Uttar Pradesh state corresponds to the highest temperature with a mean value of 31.86, followed by Tamil Nadu, Maharashtra, Andhra Pradesh, and Karnataka with mean values of 30.98, 29.89, 29.83, and 28.16, respectively. On the other hand, Maharashtra shows the highest COVID-19 cases having 2904.57 mean value, followed by Tamil Nadu, Andhra Pradesh, Karnataka, and Uttar Pradesh with mean values of 1695.64,

972.02, 855.99, and 589.51. The asymmetricity of the proposed relationship is confirmed through the JB test, where the null hypothesis “data is normally distributed” is rejected for both variables in all states. To follow up on the JB test, we have performed a BDS test of non-linearity, which reveals an in-depth distribution of data to ratify non-normality. Table 2 reports the outcome of the BDS non-linearity test, which strictly rejects the preposition of data normality across various dimensions of data (m2 to m6). As both variables (COVID-19 and temperature) are asymmetric, thus QQR is an appropriate option to unveil the quantile dependent structure (relationship). Table 3 reports the correlation analysis between COVID-19 and temperature affected states. Results shows that temperature and COVID-19 have a negative correlation in Maharashtra, Tamil Nadu, Andhra Pradesh, and Karnataka states, while for Uttar Pradesh state, temperature and COVID-19 are positively correlated.

The Quantile unit root test is used to check parameters’ stationarity in the model (see Table 4). For the array of 11 quantiles, the outcomes of the Quantile unit root have {0.05–0.95} stability scores, t-states, and critical values. We also employ ten lags of endogenous variables to avoid the drawback of the serial correlation. For the distribution quantiles of the variables, the outcomes show the existence of unit root at the level. However, the Quantile unit test validates that the parameters of the first-order difference are stationary. We investigate the likelihood of cointegration among the variables through the Quantile cointegration test, proposed by Xiao (Razzaq et al., 2020). In a similarly spaced grid of 11 quantities (0.05–0.95), the cointegration model is used. In addition, we used two leads and lags ($\Delta Z_t, \Delta Z_t^2$) in the Quantile cointegration model. Table 5 reports the coefficient of the constancy assessment of the Quantile cointegration method. The estimates show the presence of a non-linear long-run relationship between the quantiles of temperature and COVID-19.

4.2. Results of QQR analysis

The QQR methodology is used to examine the impact of temperature on COVID-19 spread in India. The QQR slope estimates $\beta_1(\theta, \tau)$ are presented in Fig. 4, demonstrating the state-wise 3D graphs. The temperature effect (x-axis) on the COVID-19 cases (y-axis) is displayed in the first column. The empirical outcomes of QQR estimation ratify that the association between COVID-19 and temperature has heterogeneity among each state. Depending on θ , the slope estimates $\beta_1(\theta, \tau)$ may vary with τ .

For Maharashtra, the overall effect of temperature on COVID-19 spread is positive. At higher quantiles (0.7–0.85), the temperature has a strong positive effect on COVID-19, while this impact is less strong among the middle quantiles of temperature. On another surface of the graph, it is evident that temperature is negatively impacted by COVID-19 at initial quantiles (0.05–0.1). However, this negative impact gets weaker at the higher quantiles for both variables. From quantile (0.2–0.35), a comparatively stronger COVID-19 effect on temperature

Table 2
BDS test results for non-linearity.

States	m = 2	p-value	m = 3	p-value	m = 4	p-value	m = 5	p-value	m = 6	p-value
Temperature										
Maharashtra	23.72	0.000	22.70	0.000	23.56	0.000	23.79	0.000	24.16	0.000
Tamil Nadu	42.89	0.000	38.75	0.000	37.16	0.000	41.24	0.000	39.10	0.000
Andhra Pradesh	17.51	0.000	18.16	0.000	19.76	0.000	18.53	0.000	20.12	0.000
Karnataka	14.30	0.000	14.09	0.000	15.39	0.000	14.86	0.000	15.82	0.000
Uttar Pradesh	19.64	0.000	18.88	0.000	19.69	0.000	19.89	0.000	20.32	0.000
COVID-19 cases										
Maharashtra	19.60	0.000	20.20	0.000	18.59	0.000	18.26	0.000	18.05	0.000
Tamil Nadu	27.76	0.000	28.54	0.000	27.21	0.000	27.19	0.000	27.47	0.000
Andhra Pradesh	19.40	0.000	19.67	0.000	17.76	0.000	16.97	0.000	16.33	0.000
Karnataka	19.90	0.000	20.91	0.000	19.84	0.000	20.05	0.000	20.50	0.000
Uttar Pradesh	19.46	0.000	19.59	0.000	17.59	0.000	16.70	0.000	15.87	0.000

Null hypothesis: Data is linear (null of linearity is rejected across all five dimensions).

Table 3
Results of correlation analysis between temperature and COVID-19.

States	Correlation	t-value	p-value
Maharashtra	-0.439148	5.845241	0.000
Tamil Nadu	-0.757951	13.89488	0.000
Andhra Pradesh	-0.488167	6.688765	0.000
Karnataka	-0.728709	12.72457	0.000
Uttar Pradesh	0.072734	0.087208	0.000

can be observed with the link across all the temperature quantiles. Maharashtra state is situated in a low temperature region, which is the major reason of this effect. Tan et al. (2005) reported that during the 2003 SARS epidemic, the risk for increased daily cases was eighteen times more in regions where the temperature was low, compared with regions having high temperatures.

In the case of Tamil Nadu, COVID-19 sprad is negatively impacted by temperature except at higher quantiles (0.6–0.95), with the link across almost all the quantiles for temperature (i.e., 0.05–0.8). At higher quantiles (0.85–0.95), there is comparatively a strong positive temperature influence on COVID-19, which indicates that when the temperature is higher than the medium quantile, the more COVID-19 cases prompt up. These findings are consistent with the latest research outcomes by (Ma et al., 2020). For Andhra Pradesh state, the figure is displaying that COVID-19 is positively impacted by temperature. This impact gets stronger at higher quantiles (0.8–0.9), with the link across all the quantiles for COVID-19. The figure also displays a comparatively weaker effect on the initial quantiles (0.05–0.1) of temperature. These outcomes are echo the findings of (Tosepu et al., 2020).

In the case of Karnataka, there is an overall weak yet positive temperature effect on COVID-19 spread. The main part of the graph, except for some upward spikes, shows a slightly positive effect. A relatively strong and positive impact of temperature is found at initial quantiles (0.05–0.15). From the higher quantiles (0.6–0.95), the effect is strongest, and a comparatively lower effect can be observed for the lower quantiles of COVID-19 with the link across all the quantiles of temperature. The possible cause of this positive association between COVID-19 and temperature in Karnataka state is the low temperature, which increases the chances of COVID-19 proliferation.

In the case of Uttar Pradesh, a highly strong and negative effect of temperature on COVID-19 is observed at initial quantiles (0.05–0.1) as reported by (Rouen et al., 2020); however, a weak positive effect is found at higher quantiles (0.9–0.95). The higher quantiles are indicating minor positive effects for both temperature and COVID-19. Uttar Pradesh is one of the warmest Indian states and according to previous findings of Merlo et al. (2006), daily infections reduce at high-temperature regions compared with low-temperature areas.

Table 4
Results of the Quantile unit root test.

Quantile	Maharashtra			Tamil Nadu			Andhra Pradesh			Karnataka			Uttar Pradesh		
	TEMP	COVID-19	t-stats	TEMP	COVID-19	t-stats	TEMP	COVID-19	t-stats	TEMP	COVID-19	t-stats	TEMP	COVID-19	t-stats
	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats
0.05	1.013	0.546	-1.163	0.966	-1.864	-1.276	0.964	0.964	-2.367	0.927	-2.373	-1.527	0.956	0.973	-0.775
0.10	0.973	-1.507	-1.446	0.981	-0.983	-0.657	0.986	0.986	-1.191	0.947	-2.642	-1.191	0.976	0.979	-1.323
0.20	0.967	-2.46	-1.847	0.988	-1.241	0.219	1.002	1.002	-1.899	0.966	-1.642	-0.816	0.992	0.97	-2.477
0.30	0.979	-1.372	-1.268	0.991	-0.693	1.002	1.002	1.002	-1.899	0.985	-0.849	-1.804	0.982	0.976	-1.285
0.40	0.983	-2.019	-1.437	1.029	2.496	-0.609	0.988	0.988	0.857	0.986	-0.724	-0.419	0.988	0.977	-1.712
0.50	0.978	-0.799	-1.681	0.966	-2.015	0.937	1.065	1.065	1.003	0.958	-2.252	-0.566	0.99	0.968	-1.509
0.60	0.988	-1.266	-2.113	0.989	-1.438	0.972	0.972	0.972	-0.995	0.972	-2.004	-1.141	0.993	0.993	-0.57
0.70	1.002	0.312	-0.772	1.100	-0.105	0.991	0.991	0.991	-0.644	0.991	-0.96	-1.856	1.007	1.007	0.709
0.80	1.009	1.189	-0.005	1.008	0.893	-0.395	0.989	0.989	-1.362	1.017	1.193	-1.503	0.992	0.995	-0.339
0.90	1.024	1.762	1.096	1.005	0.528	0.172	1.008	1.008	-0.924	1.052	3.332	-0.918	0.988	0.992	-0.551
0.95	1.001	0.187	-1.296	0.99	-2.127	1.005	1.005	1.005	0.278	0.941	-0.805	0.754	1.031	0.985	-1.701

Notes: The table shows point estimates and t-statistics values for the 5% significance level. Here the t-statistic is numerically smaller than the critical value so we reject the null hypothesis of $\alpha(\tau) = 1$ at the 5% level.

Table 5
Results of the Quantile cointegration test.

Maharashtra					
Model	Coeff.	Sup _r V _n (τ)	CV1	CV5	CV10
COVID-19 _t vs. TEMP _t	β	3,078.264	2,108.647	1,846.347	1,438.225
	α	894.331	708.105	563.318	408.389
Tamil Nadu					
Model	Coeff.	Sup _r V _n (τ)	CV1	CV5	CV10
COVID-19 _t vs. TEMP _t	β	1,825.334	1,412.089	1,120.347	896.316
	α	795.028	685.318	534.387	423.241
Andhra Pradesh					
Model	Coeff.	Sup _r V _n (τ)	CV1	CV5	CV10
COVID-19 _t vs. TEMP _t	B	4,255.292	3,593.489	2,326.722	1,948.466
	α	122.298	102.339	60.773	48.916
Karnataka					
Model	Coeff.	Sup _r V _n (τ)	CV1	CV5	CV10
COVID-19 _t vs. TEMP _t	β	6,152.755	3,157.881	2,385.316	1,948.987
	α	176.171	79.851	56.601	50.017
Uttar Pradesh					
Model	Coeff.	Sup _r V _n (τ)	CV1	CV5	CV10
COVID-19 _t vs. TEMP _t	B	5,631.058	3,514.815	3,377.57	3,328.695
	α	1,132.562	952.336	825.326	817.845

4.3. Checking the validation of the QQR method

The QQR method is used in the present study to scrutinize the τ^{th} quantile of temperature on θ^{th} COVID-19 quantile at discrete values of corresponding quantiles. Thus, this method is all-inclusive to acquire the asymmetric temperature effect on COVID-19 through the intermediate quantiles of τ and θ . To ratify the research outcomes of the QQR method, the slope parameters' mean values concerning QQR must be almost the same as that of conventional quantile regression. Precisely, the quantile regression module represented by θ could be produced by using a QQR parameter averaging along τ . The following formula is used to get the quantile regression of the model slope coefficient. It determines the effect of temperature on the dispersion of COVID-19 and denoted by $\delta_1(\theta)$ as:

$$\delta_1(\theta) = \bar{a}_1(\theta) = \frac{1}{S} \sum \tau a_1(\theta, \tau) \tag{10}$$

Here, $\frac{1}{S}$ is the amount of quantiles and $\tau = [0.10, 0.15, \dots, 0.90]$ considered. A comparison between quantile regression and QQR is illustrated in Fig. 5 that verify the previous results of QQR and ensures the same tendencies. The average values of QQR coefficients (as shown in the graphs of all states) are nearly similar to the coefficients of quantile regression and move with the same pattern. The estimates of quantile regression, as depicted in Fig. 5, could be recuperated from the complete information provided in QQR estimates.

5. Conclusions and policy propositions

This paper attempts to scrutinize the impact of temperature on COVID-19 spread in the five most affected states of India. The present research has employed the novel QQR method to verify how the quantiles of COVID-19 are affected by the quantiles of temperature and offer valuable outcome compared to the conventional quantile regression methods. Research findings illustrate heterogeneous results among syndicated regions as modeled by temperature and COVID-19 quantiles, specifying asymmetric behavior as projected by the QQR method. A significant positive impact of temperature on COVID-19 spread is found in the three Indian states (Maharashtra, Andhra Pradesh, and Karnataka), primarily at both low and high tails, whereas, Tamil Nadu and Uttar Pradesh states show a mixed trend, as the lower quantiles indicate a negative effect; however, this negative effect becomes weak at middle

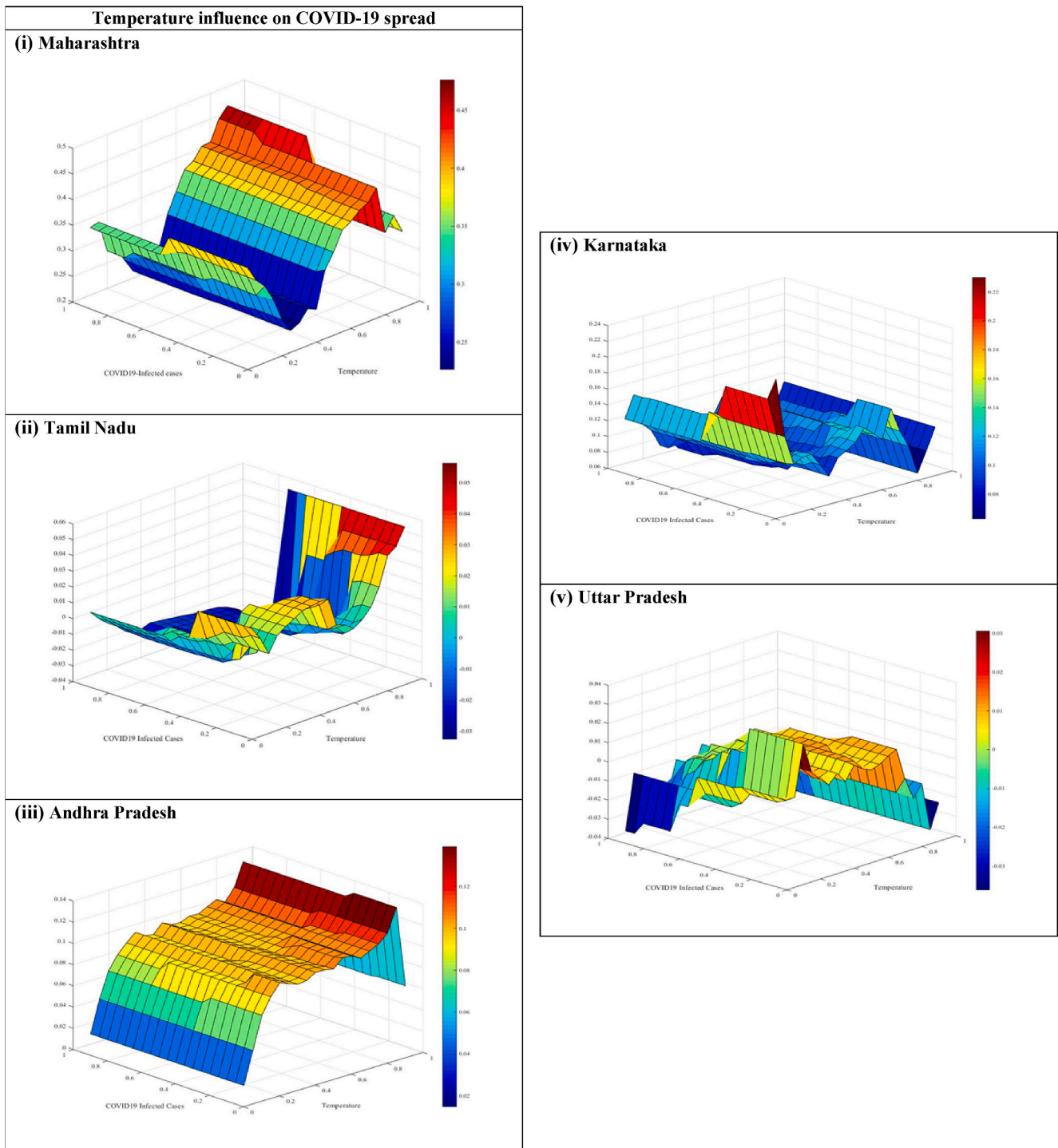


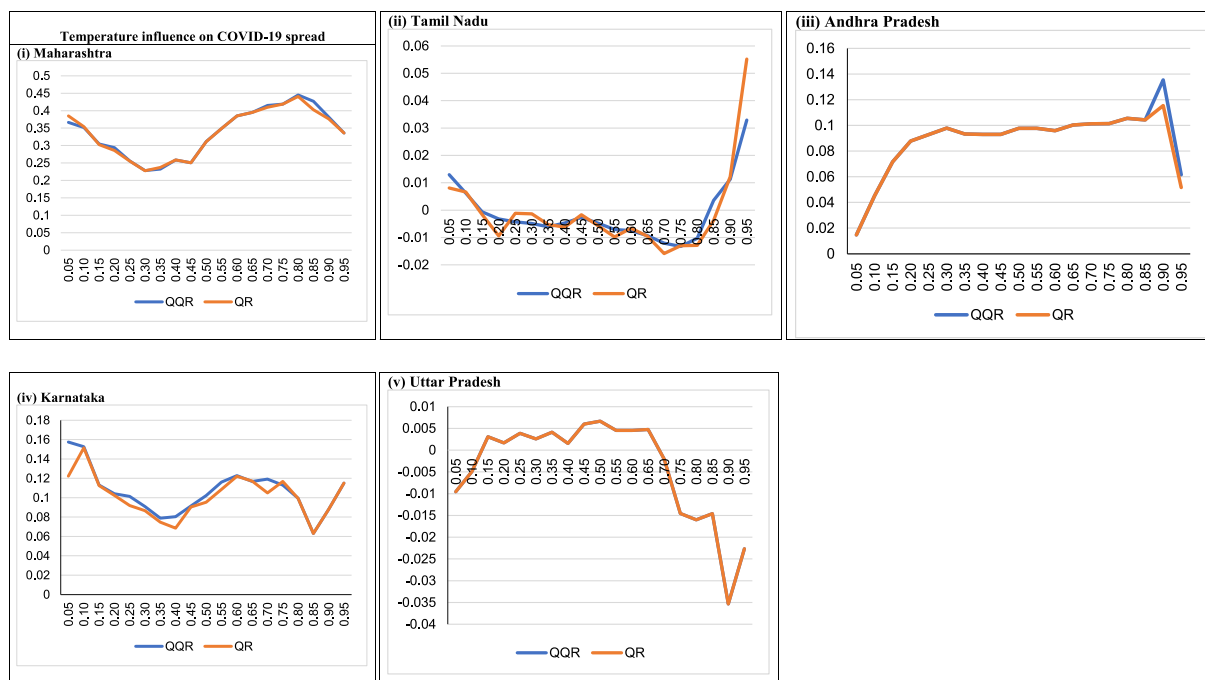
Fig. 4. The QQR estimations of the slope coefficient, $\hat{\beta}_1(\theta, \tau)$.

Notes: The graphs show the estimates of the slope coefficient $\beta_1(\theta, \tau)$ in the z-axis against the quantiles of COVID-19 in the y-axis and the quantiles of Temperature in the x-axis and vice versa.

quantiles in both states. The higher quantiles in Tamil Nadu show a strong positive effect. On the other hand, a weak but positive effect is observed at the higher quantiles of Uttar Pradesh state. One possible reason for this mixed trend can be described by variations in temperature, distinct stringency measures and population density.

The temperature has a critical function in regulating the pandemic dilemma, as COVID-19 cases increase with low temperature, while decrease as the temperature goes up. These empirical findings corroborate prior studies, as Ma et al. (2020) discovered a positive correlation

between daily temperature and COVID-19 in the Chinese city of Wuhan. Dadbakhsh et al. (2017) reported that low temperature increases the mortality rate of respiratory illnesses. Another study discovered that both cold and heat impacts may have a detrimental effect on respiratory morbidity (Li et al., 2019). Yoshino et al. (2020) investigated the connection between acclimatization and immunological function and found that low temperatures may impair immune function. Couto et al. (2018) found that inhaling cold weather promotes alveolar shrinking that cause vulnerability to lung infection. Additionally, the novel virus is



Quantiles of COVID-19

Fig. 5. Comparative analysis between QQR and QR estimates.

Notes: The red line represents the standard quantile regression (QR) parameters. In contrast, the average QQR parameters are represented by a blue line at different temperatures and COVID-19 quantiles for the five Indian states. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

heat-sensitive that has a tough time surviving in high-temperature environments (Ma et al., 2020). Lin et al. (2018) noticed that low temperature is linked with the decline of lung function. Temperature fluctuations have significant impacts on human health, including morbidity and mortality (Liu et al., 2020). Besides, the sudden temperature variations increase the burden of heart and lungs, leading to cardiopulmonary incidents (Sharafkhani et al., 2019). Other possible reasons for COVID-19 spread in these states besides temperature are the unavailability of proper medical facilities and the failure of expected human behaviors, including the lack of face mask-wearing, hand washing, social distancing, and isolation from infected individuals during the pandemic.

The aftereffects of the novel SARS-CoV-2 epidemic are very devastating in our lives, communities, and economic development, as a sudden increase in worldwide unemployment skewed social and economic balance. It is imperative that jobs should be created and the healthcare system should be developed sustainably (Ahmad et al., 2021b). This may help to the creation of jobs and offer the foundation for a long-term recovery, if the government commits to addressing climate (Tanveer et al., 2021). Economies, like Pakistan and Nepal have established various initiatives to assist the governments' "Green Wagers scheme" to instigate fiscal support by plantings trees and ecosystem renovation. Furthermore, the forest community can also increase their livelihoods by the sustainable harvest of timber and other products in the present condition with a greater emphasis on forestry programs. Besides, building sustainable facilities across deteriorated public spots may generate green jobs and increase ecological resilience (Razzaq et al., 2021; Wang et al., 2021).

Though the paper has derived some novel findings, it is not without limitations that should be addressed during future works. Firstly, the current research has only considered India's highly affected states and overlooked the other states and regions. Potential future studies should be carried out to cover other parts of the country. Secondly, we did not find the impact of air pollutants such as CO₂, particulate matter (PM_{2.5},

PM₁₀), and O₃ on COVID-19 cases. Future researchers can overcome this limitation by conducting a comprehensive study to scrutinize their influence on COVID-19. Finally, examining the impact of lockdown on environmental pollution and its association with sustainability would be an interesting future research.

Author statement

Muhammad Irfan: Conceptualization, Data Curation, Methodology, Formal analysis, Software, Writing - Original Draft, Writing - Review & Editing, Visualization, **Asif Razzaq:** Writing-Review & Editing, **Wanich Suksatan:** Writing-Review & Editing, **Arshian Sharif:** Methodology, Formal analysis, Software, **Rajvikram Madurai Elavarasan:** Data Curation, Writing-Review & Editing, **Chuxiao Yang:** Validation, Writing-Review & Editing, **Yu Hao:** Funding acquisition, Supervision, Writing-Review & Editing, **Abdul Rauf:** Writing-Review & Editing.

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Declaration of competing interest

The authors declare no conflicts of interest.

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