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Original Article

Non-linear spatial linkage between COVID-19 pandemic and mobility in ten countries: A lesson for future wave

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A B S T R A C T

Background: Restrictive measures enacted in response to the COVID-19 pandemic have resulted in dramatic and substantial variations in people's travel habits and behaviors worldwide. This paper empirically examines the asymmetric inter-linkages between transportation mobility and COVID-19.
Methods: Using daily data from 1st March 2020 to 15th July 2020, this study draws the dynamic and causal relationships between transportation mobility and COVID-19 in ten selected countries (i.e., USA, Brazil, Mexico, UK, Spain, Italy, France, Germany, Canada, and Belgium). To systematically analyze how the quantiles of COVID-19 (transportation mobility) affect the quantiles of transportation mobility (COVID-19), a complete set of non-linear modeling including the quantile-on-quantile (QQ) regression and quantile Granger causality in mean is applied.
Results: Our preliminary findings strictly reject the preposition of data normality and highlight that the observed relationship is highly correlated and quantile-dependent. The empirical results demonstrate the heterogeneous dependence between COVID-19 and transportation mobility across quantiles. The findings acclaim the presence of a significant positive association between COVID-19 and transportation mobility in the USA, UK, Spain, Italy, Canada, France, Germany and Belgium, predominantly at upper quantiles, but results are contrasting in the case of Brazil and Mexico. In addition, either lower or upper quantiles of both variables indicate a declining negative effect of transportation mobility on COVID-19. Furthermore, the outcomes of quantile Granger causality in mean conclude a bidirectional causal link between COVID-19 and transportation mobility for almost all sample countries. Unlike them, France has found unidirectional causality that extends from COVID-19 to transportation mobility.
Conclusions: We may conclude that COVID-19 leads to a reduction in transportation mobility. On the other hand, the empirical results quantify that excessive transportation mobility levels stimulate pandemic cases, and social distancing is one of the primary measures to encounter infection transmission. Imperative country-specific policy implications pertaining to public health, potential virus spread, transportation, and the environment may be drawn from these findings.

Introduction

A cluster of pneumonia cases with an unexplained etiology in China's central city, Wuhan, was reported for the first time on 31st December 2019, and one week later, it was detected as a contagious disease now named COVID-19 [1,2]. This new highly transmissible respiratory ailment was disseminated in China [3] and facilitated by hypermobile society and transportation hubs [4–7]. In a short time, it severely erupted in European countries (primarily Italy, France, Germany, and Spain) and Iran in March 2020 and then expanded at an exceptional rate to other countries, with the United States having by May 2020 the most patients infected [8]. By then, COVID-19 had spread exponentially across the globe, and as of 5th August 2021, there had been almost 200,840,180 confirmed infected patients and more than 4,265,903 deaths reported in 215 countries and territories [9].

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Social distancing,[1],[2] isolation, shielding, and quarantine,[3] before the pervasive accessibility of a vaccine and specific treatment, with personal preventive measures including hand washing and wearing a face mask, could endure the primary controlling modality for reducing COVID-19 spread [10–12]. These interventions were intended to minimize population mobility and contact, reducing SARS-CoV-2 transmission and protecting vulnerable groups [13]. This commentary intended to explore the gaps in COVID-19 response by assessing social distancing and mobility indices, thereby offering an enhanced understanding of the evolving pandemic in ten selected countries.

During this emergency period, every country had its own response to the epidemic. Especially in China, the spread of the disease was successfully mitigated by a nationwide coordinated effort to confine travel and social contact. In turn, the pandemic severity was underestimated by the United States [14,15]. Such distributed decision-making and variation in the compliance process led to a highly complex outbreak prevention response both in space and time. This uncertainty in response was augmented by the varying severity of the epidemic globally, with some countries approaching their peak and others in the initial stages of an outbreak [16]. Collectively, these problems present a significant challenge in determining the efficacy of social distancing initiatives. To resolve this issue, we used real-time transportation mobility data to quantify the transition of social distancing in the ten selected countries.

Prior studies examined the link between COVID-19 transmission and travel, but most of the studies are limited to investigating the infection in China. At the start of 2020, Kraemer et al. [17] found a positive correlation between COVID-19 and mobility across China's cities and illustrated that the growth rate of infection goes down when stringent control measures are instigated. Furthermore, Zhao et al. [18] found a statistically significant and positive relationship between the number of domestic departed passengers from Wuhan and confirmed infected cases in ten Chinese cities by using correlation analysis. Tian et al. [19] drew a statistical and mathematical inference of mobility and transmission control measures, also found evidence that social distancing initiatives played a vibrant role in reducing the case transmission in the cities of China. By relying on the global meta-population disease transmission model, Chinazzi et al. [20] found that local and international travel restrictions helped slow down infection transmission rates by 80% and more than 50% in and outside of China, respectively. In Italy, qualitative and projections-based studies tracked the effects of mobility habits in the spread of COVID-19 [21–23].

The previous studies affirmed that social distancing initiatives could effectively reduce transmission of infection outside of China; although, this fact still has not yet been asserted. There are qualitative and projection-based studies for social distancing that help to minimize the COVID-19 spread in countries like Italy and the United States. Still, quantitative research has not yet been conducted to captivate the asymmetric and spatial effect on the most COVID-19 affected countries to date. Therefore, the current research aims to quantify the dynamic and causal nexus between transportation mobility and COVID-19 cases based upon international evidence of the ten most affected countries by the pandemic spread.

Based upon the above-mentioned objective, this empirical research contributes to the existing literature in the following manners. To the best of our knowledge, our study is the first to investigate the non-linear spatial relationship between COVID-19 cases and transportation mobility using the unique dataset. Another significant contribution of this study was developing and constructing a transportation mobility index attribute, which integrates a unified composite index from three-dimensional mobility measures. Second, this seminal study was intended to uncover the asymmetric relation between COVID-19 and transportation mobility by employing the non-parametric quantile-on-quantile (QQ) method proposed by Sim and Zhou [24]. Thirdly, an advanced non-linear quantile Granger causality estimation suggested by Troster et al. [25] was applied. This approach is well synchronized with QQR methodology and seized the causality connection between COVID-19 and transportation mobility at the distribution of median, lower, and upper tails. The empirical results from this asymmetric causality method provided further support and validity of QQR results.

Data and methodology

Data description and trend

In this study, the dataset comprises of two variables, that is, COVID-19 and transportation mobility. For this empirical analysis, daily basis data are used for the ten selected countries (USA, Brazil, Mexico, UK, Spain, Italy, France, Germany, Canada, and Belgium) for the period from 1st March 2020 to 15th July 2020, which is a total of 135 daily observations. The current study has selected top-ten COVID-19 affected countries whose transportation mobility data was consistently available for its three modes-driving, transit and walking. These top ten countries have been selected for empirical analysis because they were most affected and had the highest number of pandemic cases at the time of data collection. Moreover, the strong connection (correlation) between transportation mobility and COVID-19 cases in these countries permits the QQ approach to better capture the asymmetric spatial relationship between two variables simultaneously.[4] The COVID-19 outbreak is signified by the "number of daily new infected and confirmed cases" of the COVID-19. The numbers of COVID-19 cases for each selected country are obtained from the official website of the European Centre for Disease Prevention and Control.[5] Fig. 1 shows the trend of daily new confirmed cases in ten selected countries. The time period for the dataset has been selected not only due to the availability of consistent data for the three modes-driving, transit, and walking, but also the peak period of the first wave of extreme COVID-19 spread and extensive social distancing and transportation immobility that occurred in these ten most-affected countries at that time. Therefore, the current study has utilized the specific case of these ten selected countries during the first wave of pandemic spread, exhibiting a solid connection between COVID-19 and transportation immobility and social distancing.

The data of transportation mobility trends are derived from Apple Mobility Trends Report.[6] The data of transportation mobility consists of three modes: driving, transit (public transport), and

[1] The concept of "quarantine and social distancing" can also be traced back to Islamic and Arab history 1300 years ago [56]. In medieval Europe, the term "quarantine" with the meaning of "forty days" comes from its Italian origin 700 years ago between the 14th–15th-century, when ships inbound in Venice had to wait for 40 days before docking in the town [57].

[2] To evade and deter the contagion like COVID-19; The Holy Prophet Muhammad (PBUH) advised quarantine and social distancing: "If you hear of an outbreak of plague in a land, do not enter it; but if the plague outbreaks out in a place while you are in it, do not leave that place" [56].

[3] "Those with contagious diseases should be kept away from those who are healthy" [56].

[4] Kindly see the following papers on QQ approach for further reference, its applicability and prerequisites [37,58].

[5] The data of COVID-19 downloaded from the website https://www.ecdc.europa.eu/en/covid-19-pandemic.

[6] The data of transportation mobility obtained from the website https://covid19.apple.com/mobility.

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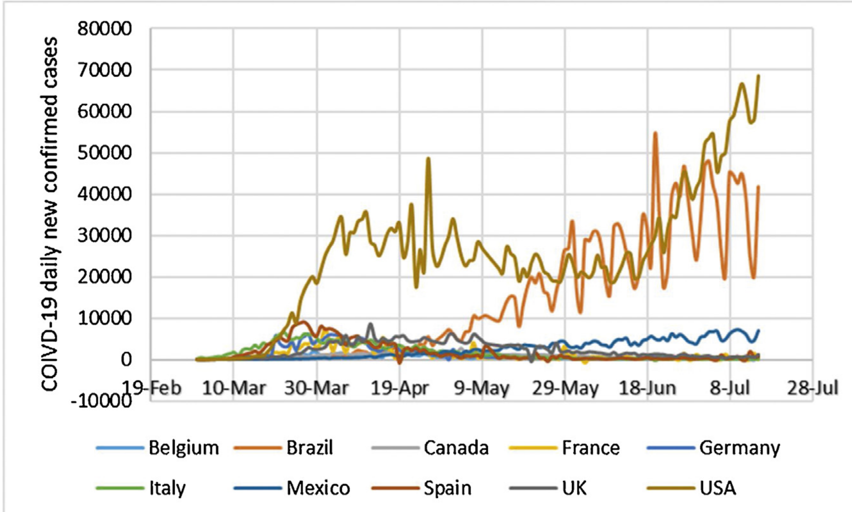

Fig. 1. Daily new confirmed cases of COVID-19 in ten selected countries.

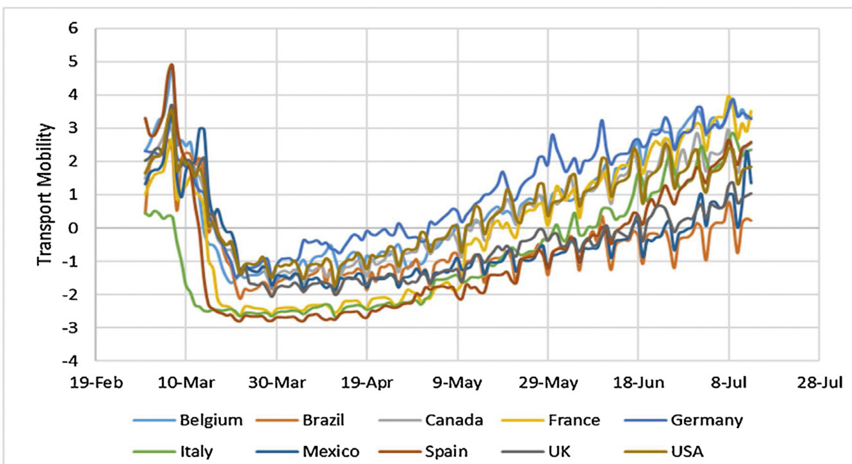

Fig. 2. Transportation mobility patterns in ten selected countries.

walking. The trend of transportation mobility in the ten selected countries is shown in Fig. 2.

We syndicate these three individual scores and develop the aggregate and composite index that we designate as TRMB [26]. An inclusive indicator of transportation mobility is articulated by exerting the Principal Component Analysis (PCA) from the above-mentioned three modes of transportation mobility, which is exerted in contemporary research. Precisely, a weighted index of driving, transit (public transport), and walking derived from PCA is the new indicator for transportation mobility. Its primary vantage is that this indicator syndicates the entirety of germane information appropriate to the three modes of transportation mobility in a single, unified and cohesive composite index [27–29].

Methodology

Quantile-on-quantile regression (QQR)

This section of the paper briefly explains the main characteristics and significance of the newly *quantile-on-quantile* regression (QQR) approach proposed by Sim and Zhou [24]. This study also delimits the model specifications used in this analysis to analyze the asymmetric relationship between confirmed and infected cases of COVID-19 and transportation mobility in the ten selected countries. This approach is better and a cut above the other traditional regression models, such as quantile regression analysis (QRA) and ordinary least squares (OLS) model [30]. Except for the regular phase of the response variable, quantile regression analysis (QRA) also illustrates specific tail dependence structure information. Therefore, this approach can seize the different magnitude of the impact of COVID-19 on transportation mobility and assorted dependence structures. Moreover, it can overlook some aspects that the essence of uncertainty may substantially affect co-dependence [31].

The QQR approach can be remarked as an abstraction of the traditional quantile regression model that allows us to determine how one variable's quantiles stimulate the contingent quantiles of the response variable. This QQR approach is theoretically founded on classical quantile regression with a combination of non-parametrical estimations [27]. First, the traditional quantile regression model, based on the empirical work of Koenker and Bassett [30], is applied to determine the effect of a particular exogenous variable (COVID-19) on varied quantiles of an explained variable (transportation mobility). Second, the typical quantile regression method preferably examines the influence of an explanatory variable (COVID-19) on an explained variable (transportation mobility) not only at the center but also at the tail and head quantiles of specified data distribution, so allowing us to determine the robust characterization between the concerned variables over various periods of time. Third, QQR utilizes the technique of local linear regression to quantify the confined properties of a particular quantile of the stimulus variable (COVID-19) on the response variable (transportation mobility) and vice versa.

Moreover, by imputing the higher weights to adjacent neighbors (quantiles), the technique of local linear regression substantially evades the question of dimensionality merely attributed to the non-parametric estimates. Thus, the amalgamation of these two methods permits us to examine the underlying linkage between quantiles of the explanatory variable (COVID-19) and quantiles of the dependent variable (transportation mobility), offering more specificity than traditional techniques of OLS or quantile regression.

In the context of this study, the QQ method is suggested to uncover the effects of different quantiles of transportation mobility (COVID-19) on the quantiles of COVID-19 (transportation mobility) of a country. The following non-parametric quantile regression model has its starting point for this approach.

$$TRMB_t = \beta^{\theta}(CV19_t) + \xi_t^{\theta} \tag{1}$$

$$CV19_t = \vartheta^{\theta}(TRMB_t) + \xi_t^{\theta} \tag{2}$$

where $CV19_t$ represents the COVID-19 (daily confirmed cases) of a specific country at period t, $TRMB_t$ represents the weighted index of transportation mobility of a country at period t, θ signifies the θth equidistant quantile of the provisional distribution of *CV19* and ξ_t^{θ} indicates the quantile residue in each equation. $\beta^{\theta}(\bullet)$ is termed as an unidentified factor with no a priori information.

This QQ model explores the divergent effects of COVID-19 across different quantiles of transportation mobility and vice versa for the ten selected countries. Flexibility is the main superior feature of the specification, and this approach can locate the functional pattern of the dependency between COVID-19 and transportation mobility. However, the main limitation concerning the quantile regression model is the non-consideration of the nature of large positive and small positive shocks resulting from transportation mobility or COVID-19, which may also influence the interconnection between COVID-19 and transportation mobility [32]. In this respect, the impact of large positive COVID-19 shocks on transportation mobility can be different from that caused by small positive COVID-19 shocks on transportation mobility and vice versa. In terms of $\beta^{\theta}(\bullet)$ unknown function, QQR applies a Taylor expansion at first-order to extend the initial regression model:

$$\beta^{\theta}(CV19_t) \approx \beta^{\theta}(CV19^{\tau}) + \beta^{\theta^*}(CV19^{\tau})(CV19_t - CV19^{\tau}) \tag{3}$$

where β^{θ^*} denotes the partial derivative of $\beta^{\theta}(CV19_t)$ concerning CV19 shocks; it also measures the marginal response of CV19. Nonetheless, it represents an identical interpretation of the slope coefficient within the linear regression model framework. To capture the asymmetric effects of quantiles of TRMB on quantiles of $CV19_t$, the prior Eq. (2) can be modified and expanded. For this, Eq. (4) assumes a first-order Taylor expression, as used in Eq. (3):

$$\vartheta^{\theta}(\mathrm{TRMB}_t) \approx \vartheta^{\theta}(\mathrm{TRMB}^{\tau}) + \vartheta^{\theta^*}(\mathrm{TRMB}^{\tau})(\mathrm{TRMB}_t - \mathrm{TRMB}^{\tau}) \tag{4}$$

where ϑ^{θ^*} calculates the partial differential of $\vartheta^{\theta}(\mathrm{TRMB}_t)$ with reference to TRMB shocks. ϑ^{θ^*} is also labeled as the marginal effect of TRMB. Moreover, in a modeling framework for linear regression, ϑ^{θ^*} provides a similar explanation of the slope parameter.

A top-notch feature of Eq. (3) is that the parameters $\beta^{\theta}(CV19^{\tau})$ and $\beta^{\theta^*}(CV19^{\tau})$ are double indexed in θ and τ. In addition, $\beta^{\theta}(CV19^{\tau})$ and $\beta^{\theta^*}(CV19^{\tau})$ are the respective functions of θ and $CV19^{\tau}$ and that $CV19^{\tau}$ another function of τ. Therefore, $\beta^{\theta}(CV19^{\tau})$ and $\beta^{\theta^*}(CV19^{\tau})$ are the functions of equidistant quantiles, of considered variables, θ and τ, respectively. In this way, $\beta^{\theta}(CV19^{\tau})$ and $\beta^{\theta^*}(CV19^{\tau})$ can be re-written as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$ respectively.

Eq. (3) can be re-written:

$$\beta^{\theta}(CV19_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(CV19_t - CV19^{\tau}) \tag{5}$$

A compelling feature of Eq. (4) is that the parameters $\vartheta^{\theta}(TRMB^{\tau})$ and $\vartheta^{\theta^*}(TRMB^{\tau})$ are dual indexed in θ and τ. Additionally, $\vartheta^{\theta}(TRMB^{\tau})$ and $\vartheta^{\theta^*}(TRMB^{\tau})$ represents functions of θ and $TRMB^{\tau}$ and that $TRMB^{\tau}$ implies a function of τ. Thus, $\vartheta^{\theta}(TRMB^{\tau})$ and $\vartheta^{\theta^*}(TRMB^{\tau})$ denotes functions of θ and τ, respectively. So, $\vartheta^{\theta}(TRMB^{\tau})$ and $\vartheta^{\theta^*}(TRMB^{\tau})$ can be renamed as $\vartheta_0(\theta, \tau)$ and $\vartheta_1(\theta, \tau)$ respectively.

Eq. (4) can be re-written:

$$\vartheta^{\theta}(\mathrm{TRMB}_t) \approx \vartheta_0(\theta, \tau) + \vartheta_1(\theta, \tau)(\mathrm{TRMB}_t - \mathrm{TRMB}_t^{\tau}) \tag{6}$$

By substituting Eq. (5) in Eq. (1), the following equation is obtained:

$$TRMB_t = \underbrace{\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(CV19_t - CV19^{\tau})}_{*} + \xi_t^{\theta} \tag{7}$$

By replacing Eq. (6) into Eq. (2), the new regression model is:

$$CV19_t = \underbrace{\vartheta_0(\theta, \tau) + \vartheta_1(\theta, \tau)(TRMB_t - TRMB^{\tau})}_{*} + \xi_t^{\theta} \tag{8}$$

The underlined part (∗) of Eqs. (7) and (8) represents the θth provisional quantile of TRMB and *CV19*. These expressions contemplate the varying properties of the τth quantiles of CV19 on the θth quantiles of the TRMB in Eq. (7) and vice versa in Eq. (8). These parameters can be seen to vary in terms of different quantiles. Besides addressing the minimization problem, we replace the estimated local linear regression parameters of CV19 from b_0 and b_1 to β_0 and β_1. Now we can get Eq. (9) by measuring the problem of minimization:

$$\min_{b_0, b_1} \sum_{i-1}^{n} \psi\theta \left[TRMB_t - b_0 - b_1(C\hat{V}19_t - C\hat{V}19^{\tau}) \right] \times R\left(\frac{K_n(C\hat{V}19_t) - \tau}{l} \right) \tag{9}$$

For measuring the impact of TRMB on CV19 in Eq. (10), the relevant minimization problem can be extracted.

$$\min_{b_0, b_1} \sum_{i-1}^{n} \psi\theta \left[CV19_t - b_0 - b_1(TR\hat{M}B_t - TR\hat{M}B^{\tau}) \right] \times R\left(\frac{K_n(TR\hat{M}B_t) - \tau}{l} \right) \tag{10}$$

where $\psi\theta(u)$ signifies the quantile loss function and represented as $\psi\theta(u) = u(\theta - I(u < 0))$, while I is a standard indicator function. $R(\bullet)$ denotes the Gaussian kernel function and l is the bandwidth parameter of related kernel distribution. We use the Gaussian kernel to measure the CV19 (or TRMB) neighborhood observations, as this kernel is very efficient and extensively used in QQ regression. Moreover, these parameters are inversely related to distant conjectures of the distribution function of $C\hat{V}19_t$ denoted by $K_n\left(C\hat{V}19_t\right) = \frac{1}{n}\sum_{r=1}^{n} I\left(C\hat{V}19_r < C\hat{V}19_t\right)$ and distribution function of $TR\hat{M}B_t$ represented by $K_n\left(TR\hat{M}B_t\right) = \frac{1}{n}\sum_{r=1}^{n} I\left(TR\hat{M}B_r < TR\hat{M}B_t\right)$, and provide the value of these distribution functions, which ultimately integrate with the quantile $CV19^{\tau}$ and quantile $TRMB^{\tau}$, respectively, stated by τ. From the previous studies, the 5% bandwidth parameter is utilized in this empirical study to provide an optimal blend of variance and permitted bias [24,33–35].

Checking the validity of the QQ method

The present research applied the QQR approach to examine the τth COVID-19 (CV19) quantile on θth quantiles of transportation mobility (TRMB) and vice versa at distinct values of the particular quantiles. Consequently, this method has more depth in estimating the asymmetric effect of COVID-19 (transportation mobility) on transportation mobility (COVID-19) through equidistant quantiles of both τ and θ. Therefore, to verify the findings of the QQR method in the previous section, the average estimates of slope coefficients related to quantile-on-quantile regression should be almost equivalent to those of conventional quantile regression analysis. Considering the decomposition properties implicit in the QQR model, the QQR approximation is typically applied to extract the estimation from the traditional quantile regression [24,36]. Precisely, averaging the QQ parameter along τ can produce the quantile regression parameter, which is only represented by θ. For instance, with the given formula, the slope coefficient, which estimates the effect of COVID-19 on transportation mobility, of the QQR model, can be expressed as:

$$\lambda_1(\theta) \equiv \overline{\hat{\beta}_1}(\theta) = \frac{1}{S}\sum_{\tau} \hat{\beta}_1(\theta, \tau) \tag{11}$$

where $\frac{1}{S}$ denotes the respective number of quantiles, and τ = [0.10, 0.15, . . ., 0.90, 0.95] considered.

Quantile Granger causality approach

For the asymmetric causal relationship between COVID-19 and transportation mobility, we employed the quantile Granger causality method introduced by Troster et al. [25] in conjunction with the QQR approach across the defined h = 0,05 bandwidth parameter. The fundamental purpose of these causal estimates is to ensure the robustness of the previous findings and assess the unidirectional or bidirectional causal link between COVID-19 and transportation mobility in the ten selected countries. Following the empirical study of Hashmi et al. [37], the econometric formulation of the quantile Granger causality is as following:

$$H_0^{Y \to X} : F_X(x|M_i^x, M_i^y) = F_X(x|M_i^x), \tag{12}$$

where $F_X(x|M_i^x, M_i^y)$ is the provisional dispersion function of X_i, contingent on the composite vector of $(M_i = M_i^x, M_i^y)$. We use the D_T test to validate a null hypothesis in Eq. (13) under quantile autoregression framework (QAR) as defined by $m(\bullet)$ following the work of Troster et al. (2018) so that values are $\pi \in \Pi \subset [0, 1]$.

$$QAR(1) = m^1(M_i^X, \delta(\pi)) = \xi_1(\pi) + \xi_1(\pi)X_{i-1} + \mu_i \Omega_\propto^{-1}(\pi) \tag{13}$$

The QAR function uses the absolute probability method to measure values within a quantile matrix's uniform space $\delta(\pi) = \xi_1(\pi) + \xi_1(\pi) = \Omega_\propto^{-1}$ as provisional dispersion's transitional function. To fix the cause sign between the variables, we utilize Eq. (13) to extend the lag values in order to measure quantile autoregressive frameworks. The final equation for QAR(1) model is revised as follows:

$$Q_\pi^X(X_i|M_i^x, M_i^y) = \xi_1(\pi) + \xi_1(\pi)X_{i-1} + \kappa(\pi)Y_{i-1} + \mu_i \Omega_\propto^{-1}(\pi) \tag{14}$$

Results and discussion

Descriptive statistics and data normality

The descriptive statistics in Table 1 summarizes the descriptive analytics for COVID-19 (number of daily confirmed and infected cases) and the weighted index of transportation mobility over the entire sample period for each selected country. The average values for COVID-19 are positive for all ten selected countries, but the average values of transportation mobility for most countries are negative. The USA is the most affected country due to the more significant number of COVID-19 cases with the highest mean value of 25134.32, varying from 3 to 68518. Brazil is second in the list with the highest average value of 14180.97, which varies from 0 to 54771. Mexico is in third place with the maximum mean value of 2481.356, which varies from 1 to 7280. Similarly, the UK, Spain, Italy, Germany, and France also have more COVID-19 cases with the highest mean values of 2327.267, 1900.481, 1784.519, 1469.474, and 1271.519, respectively. In contrast, Canada shows the lowest mean value of 786.519, which fluctuates from 0 to 2760. Also, Belgium has the lowest average value of 455.711 and extends from 0 to 2454.

Concerning transportation mobility, Germany has the highest mobility patterns with an average value of 1.105, followed by Belgium 0.707, the USA 0.494, and Canada 0.424. France, Mexico, UK, and Brazil also show a high average value at −0.039, −0.465, −0.391, and −0.595, respectively. In contrast, Spain has the lowest mean value −0.736, and it ranges between −2.804 and 4.873. Also, Italy shows the lowest mean value of −0.798, which fluctuates from −2.67 to 2.865. The standard deviation values from Table 1 indicate that transportation mobility remained impulsive and volatile in France 2.048, followed by Spain 1.942 and Belgium 1.736. The Jarque-Bera normality test shows statistically substantial results, demonstrating that COVID-19 and transportation mobility are not normally distributed in all ten selected countries.

In addition, the results of both ADF (Augmented Dickey-Fuller) and ZA [38] unit root tests indicate that both COVID-19 and transportation mobility are showing non-stationary behavior at levels and viewing stationary behavior at their first order differentials. Hence, these two selected variables are integrated at 1st difference, i.e., $I(1)$ and converted for QQR into their difference series.

Table 2
Correlation coefficients.

Country	Correlation	t-Value	p-Value
USA	−0.293***	−3.535	0.000
Brazil	−0.442***	−5.687	0.000
Mexico	−0.400***	−5.038	0.000
UK	−0.780***	−14.403	0.000
Spain	−0.585***	−8.312	0.000
Italy	−0.877***	−21.093	0.000
France	−0.594***	−8.521	0.000
Germany	−0.668***	−10.365	0.000
Canada	−0.581***	−8.245	0.000
Belgium	−0.771***	−13.972	0.000

Note: *** indicates the level of significance at a 1 percent level of significance.

Correlation coefficients

The empirical results in Table 2 enlighten the correlation coefficient's value between COVID-19 and transportation mobility in the ten selected countries. The sign of the correlation coefficient shows that COVID-19 and transportation mobility are negatively correlated in all selected countries. Italy has the highest correlation coefficient (−0.877), followed by UK (−0.780), Belgium (−0.771), Germany (−0.668), and France (−0.594). The value of correlation is also relatively high in Spain (−0.585) and Canada (−0.582). For Brazil and Mexico, the value of correlation, i.e., (−0.442) and (−0.400) respectively, is comparatively low. For the USA, the correlation parameter is (−0.293), which is very low. These correlation findings imply that COVID-19 and transportation mobility are highly associated in almost all selected countries.

QQR regression results

We have applied QQR to explore the relationship between COVID-19 and transportation mobility for ten selected countries. The slope coefficients of QQR are displayed in Fig. 3, which exhibits the country-wise asymmetric effects in three-dimensional spatial graphs in two columns. The graphs in the first column estimate the heterogeneous effect of τth quantile of COVID-19 on θth equidistant quantile of transportation mobility, as denoted by $\beta_1(\theta, \tau)$, for all ten selected countries. Correspondingly, the second strand of spa-

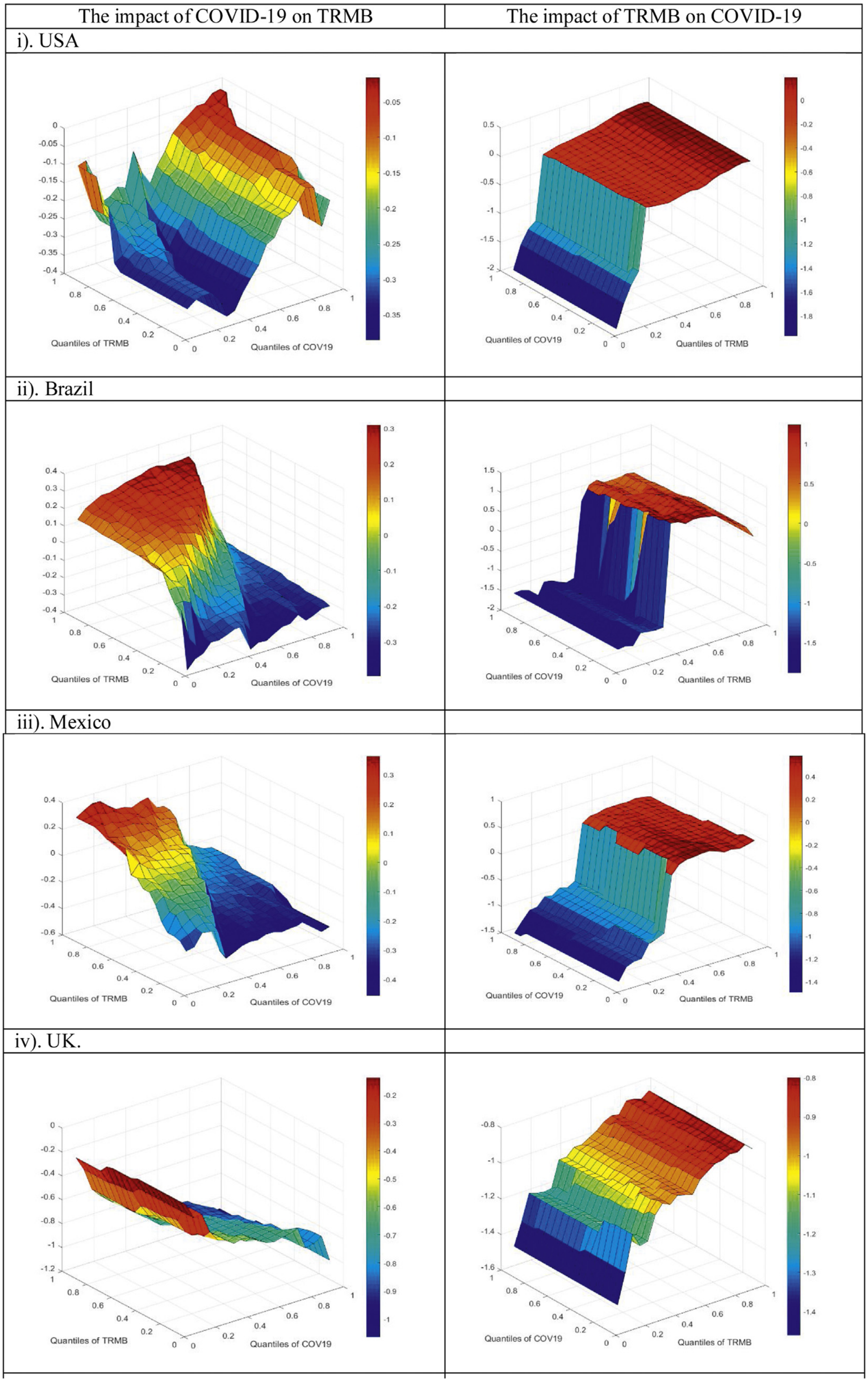

Fig. 3. Quantile-on-quantile (QQ) estimates of the slope coefficient, $\hat{\beta}_1(\theta, \tau)$.

Note: The graph displays the values of slope coefficients $\hat{\beta}_1(\theta, \tau)$ on the z-axis against the equidistant quantiles of transportation mobility along the y-axis and the equidistant quantiles of COVID-19 along the x-axis.

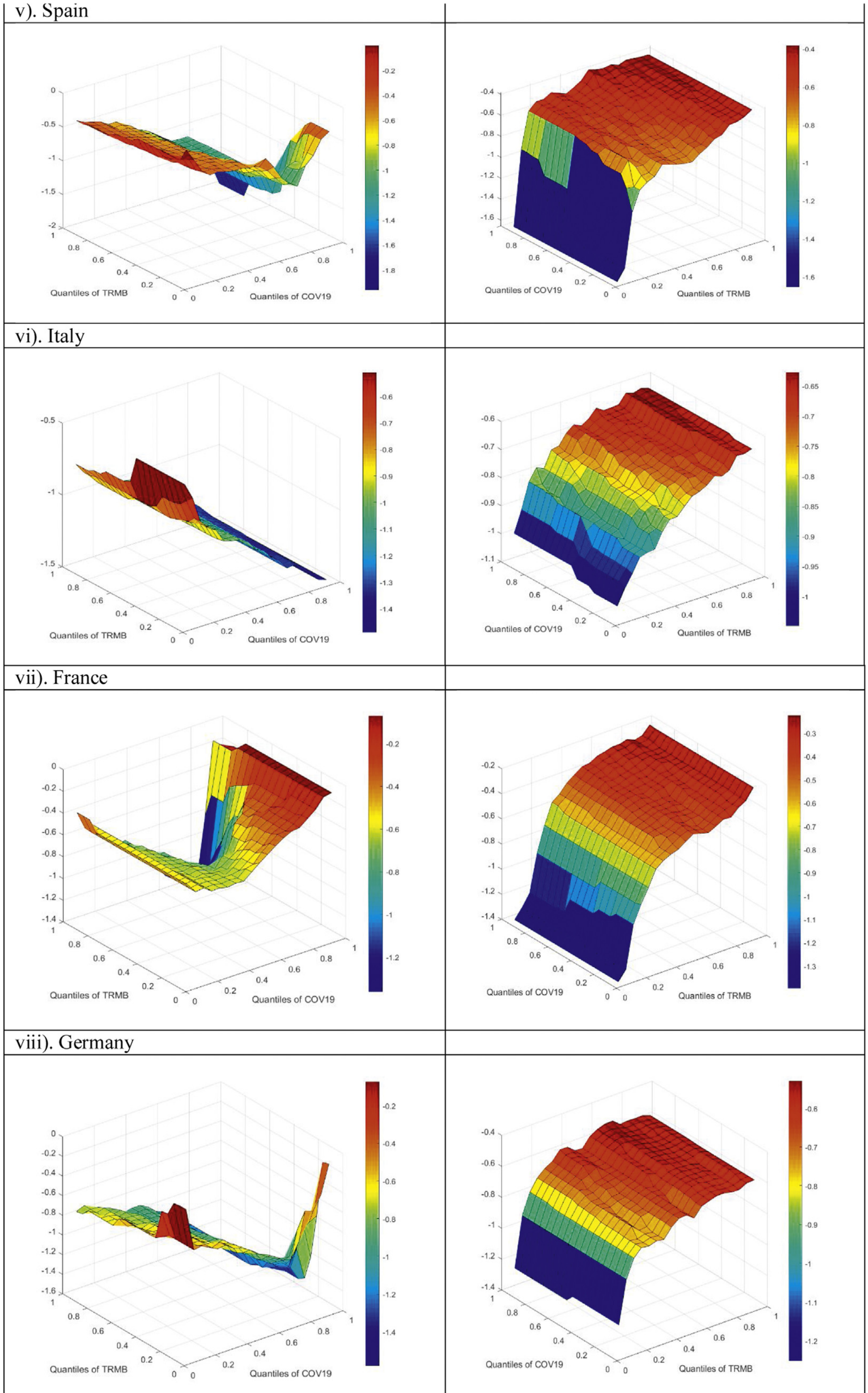

Fig. 3. (*Continued*)

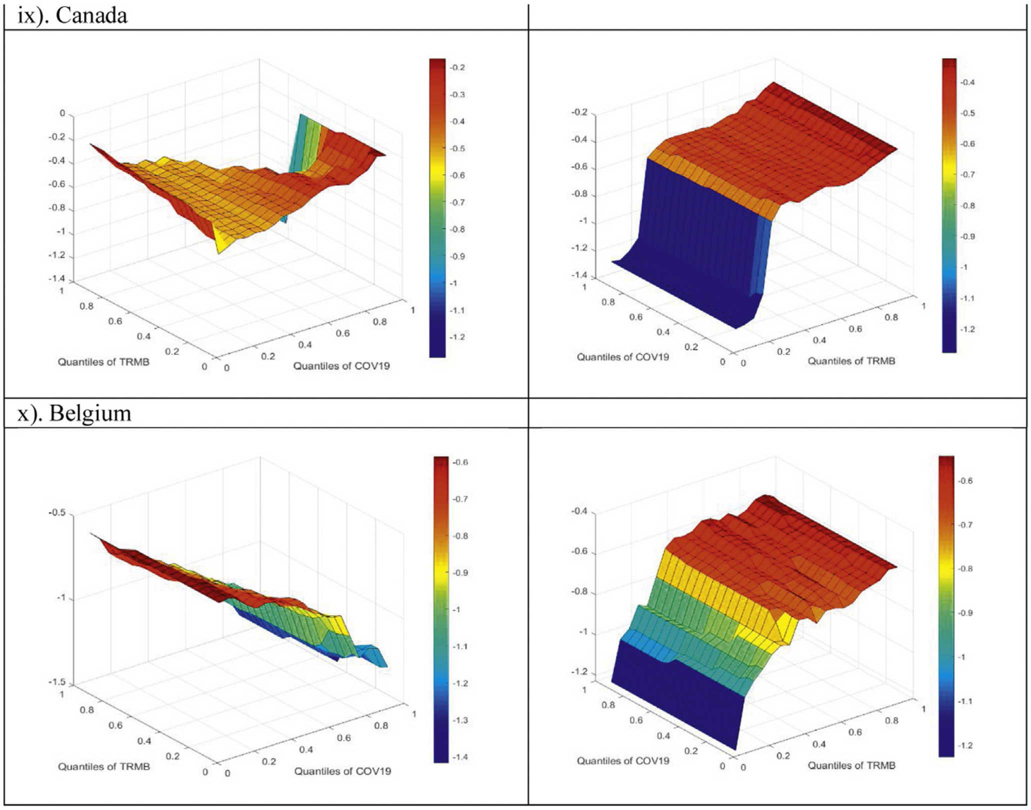

Fig. 3. (*Continued*)

tial graphs in column 2 characterizes the slope parameters $\vartheta_1(\theta, \tau)$ to examine the effect of τth equidistant quantile of transportation mobility on θth equidistant quantile of COVID-19. Evidently, QQR estimation of slope parameters in multi-dimensional spatial graphs suggests that the connection between COVID-19 and transportation mobility is not merely symmetrical. Still, the structure of these QQR relational curvatures considerably diverges across countries and time periods.

In the **USA**, an adverse effect of COVID-19 on transportation mobility is observed in the region that combines the area of the lower and upper quantiles (0.20–0.80) of COVID-19 with the lower to upper quantiles (0.2–0.95) of transportation mobility. A positive nexus between COVID-19 and transportation mobility originates at the upper and highest quantiles of COVID-19 (0.70–0.95) and the highest quantiles of transportation mobility (0.80–0.95). In both COVID-19 and transportation mobility, a strong positive linkage is

Table 1
Descriptive statistics and unit root results for COVID-19 and transportation mobility.

Country	N	Mean	Std. Dev.	Min	Max	J-B Stats	ADF-1(1)	ZA-1(1)	Break year
COVID-19									
USA	135	25134.32	15633.110	3	68,518	5.601*	−16.114***	−11.757***	12apr2020
Brazil	135	14180.97	15070.010	0	54,771	17.060***	−11.930***	−10.159***	19jun2020
Mexico	135	2481.356	2158.387	1	7280	10.490***	−12.116***	−13.740***	28may2020
UK	135	2327.267	1915.226	4	8719	11.020***	−15.173***	−10.567***	13apr2020
Spain	135	1900.481	2353.443	0	9181	58.840***	−14.568***	−15.829***	28mar2020
Italy	135	1784.519	1809.453	113	6557	20.270***	−12.824***	−11.378***	26mar2020
France	135	1271.519	1450.523	0	7578	98.700***	−17.770***	−12.470***	03apr2020
Germany	135	1469.474	1712.067	0	6294	55.860***	−15.279***	−10.860***	05apr2020
Canada	135	786.519	595.403	0	2760	6.561**	−18.104***	−11.469***	05may2020
Belgium	135	455.711	521.747	0	2454	51.070***	−17.289***	−10.789***	31mar2020
Transportation mobility									
USA	135	.494	1.267	−1.709	3.523	8.555**	−12.841***	−12.799***	23mar2020
Brazil	135	−.595	1.062	−2.123	2.64	50.040***	−15.322***	−12.696***	23mar2020
Mexico	135	−.465	1.186	−1.878	3.353	40.220***	−12.512***	−13.109***	25mar2020
UK	135	−.391	1.241	−2.054	3.652	18.600***	−12.998***	−12.286***	30mar2020
Spain	135	−.736	1.942	−2.804	4.873	15.310***	−8.369***	−6.085***	24mar2020
Italy	135	−.798	1.650	−2.670	2.865	12.480***	−8.514***	−7.359***	25mar2020
France	135	−.039	2.048	−2.611	3.976	12.210***	−12.069***	−10.219***	23mar2020
Germany	135	1.105	1.505	−1.480	3.872	10.150***	−11.345***	−11.329***	23mar2020
Canada	135	.424	1.392	−1.712	3.099	10.590***	−12.793***	−13.346***	23mar2020
Belgium	135	.707	1.736	−1.830	4.817	10.910 ***	−12.142***	−6.075***	25mar2020

*, **, *** indicates 1%, 5% and 10% level of significance.
Note: Std. Dev., standard deviation; J-B Stats, Jarque–Berra normality test.

also observed at the highest quantiles. Nevertheless, the impact of transportation mobility on COVID-19 is very condensed and negative at lower quantiles of transportation mobility and low to high quantiles of COVID-19. Furthermore, this effect is weaker at intermediate quantiles of COVD-19 and then gets more assertive at the upper quantiles of COVID-19. Overall, these findings reveal that COVID-19 has a negative impact on transportation mobility, and we may conclude that COVID-19 leads to a reduction in transportation mobility. However, transportation mobility has a rising stimulating effect on the spread of COVID-19. The positive effect of transport mobility is more pronounced in its higher quantiles; the higher level of transportation mobility causes more spread of the pandemic in the USA, which is an alarming sign. These empirical outcomes are consistent with Badr et al. [14], who reported that mobility patterns are highly correlated with COVID-19 cases.

In the case of **Brazil**, a strong adverse can be visualized at the upper extreme quantiles of COVID-19 on transportation mobility. An adverse impact of COVID-19 on transportation mobility is originated in the region that syndicates the lower to upper quantiles (0.05–0.95) of COVID-19 with the lower quantiles (0.05–0.40) of transportation mobility. A robust positive nexus between COVID-19 and transportation mobility is found at the upper and highest quantiles of COVID-19 (0.50–0.95) and medium to upper quantiles of transportation mobility (0.70–0.95). Conversely, the U-shaped impact of transportation mobility on COVID-19 is very condensed and negative at lower to medium quantiles of transportation mobility and low to high quantiles of COVID-19. Nevertheless, this weaker effect weaker is observed at intermediate quantiles (0.50−0.60) of COVD-19 and then gets more assertive at the upper and extreme quantiles (0.70−0.95) of our response variable, COVID-19. Overall, these findings reveal that COVID-19 has a negative impact on transportation mobility, while transportation mobility has a rising positive effect on COVID-19. In Brazil, when transportation mobility patterns are low, the COVID-19 cases are in small numbers, and when transportation mobility is increasing, later COVID-19 cases are growing in massive amounts. To be precise, we may conclude that COVID-19 reduces transportation mobility, while higher mobility increases pandemic cases in Brazil. These results are in line with the findings of Zhu et al. [39] and Mellan et al. [40] reported that mobility patterns are highly correlated with COVID-19 infection.

In **Mexico**, the effect of COVID-19 on transportation mobility is substantial or even detrimental at medium to upper quantiles of COVID-19. A contrary effect of COVID-19 on transportation mobility is established in the region that syndicates the region of medium and upper quantiles (0.50–0.95) of COVID-19 with the lower to middle quantiles (0.20–0.50) of transportation mobility. A little positive effect of COVID-19 on transportation mobility is instigated at the upper and highest quantiles of COVID-19 (0.80–0.95) and the highest quantiles of transportation mobility (0.60–0.95). More profoundly, an adverse effect of COVID-19 on transportation mobility is observed at the lower to upper quantiles, but a positive effect is also found in upper quantiles. On the other side, the impact of transportation mobility on COVID-19 is very condensed and negative at lower quantiles of transportation mobility and low to high quantiles of COVID-19. Although, this effect becomes weaker at intermediate quantiles of COVD-19 and then appears strong at the upper quantiles of COVID-19. In summing up, these findings reveal that COVID-19 has an overall negative impact on transportation mobility, and transportation mobility has a rising positive effect on COVID-19. These empirical results are aligned with the recent findings of Vinceti et al. [41], who reported that mobility patterns are highly inverse correlated with COVID-19 cases.

In the **UK**, the effect of COVID-19 on transportation mobility is minor or even hostile at the upper quantiles of COVID-19. An argumentative impact of COVID-19 on transportation mobility is originated in the region that syndicates the higher quantiles (0.70–0.95) of COVID-19 with the upper quantiles (0.70–0.95) of transportation mobility. The spread of COVID-19 has a relatively strong positive influence on transportation mobility at the upper and highest quantiles of COVID-19 (0.60–0.95) and upper quantiles of transportation mobility (0.80–0.95). On the other side, the impact of transportation mobility on COVID-19 is significantly shortened and negative at lower to medium quantiles (0.20−0.70) of transportation mobility and low to high quantiles (0.20−0.95) of COVID-19. Nevertheless, a weaker effect is observed at intermediate quantiles (0.50−0.60) of COVD-19 and then becomes positively strong with a rising magnitude in the vicinity of higher quantiles (0.70−0.95) of the COVID-19 pandemic. Overall, these findings reveal that COVID-19 has a negative impact on transportation mobility. In comparison, transportation mobility has a rising positive effect on COVID-19. In short, we may conclude that COVID-19 leads to a reduction in transportation, and a higher level of transport mobility causes the spread of the pandemic in the UK. The results of the impact of COVID-19 on transportation mobility are in line with the findings of Zhu et al. [42], who reported that mobility patterns are highly correlated with COVID-19 infection.

In **Spain**, there is a declining negative effect of COVID-19 on transportation mobility. A relatively weak negative effect of COVID-19 on transportation mobility is instigated at the lower and medium quantiles of COVID-19 (0.05–0.70) and the highest quantiles of transportation mobility (0.80–0.95). The weakest effect can also be found at upper and higher quantiles of COVID-19 (0.75–0.95) and upper quantiles of transportation mobility. A negative impact of COVID-19 on transportation mobility is found in the region of upper quantiles (0.80−0.95) of COVID-19 with upper quantiles (0.70–0.95) of transportation mobility. In contrast, the condensed and negative effect of transportation mobility on COVID-19 is found in the syndicated region formed by lower quantiles of transportation mobility (i.e., 0.05–0.20) and almost all quantiles of COVID-19 (0.05–0.95). The effect of transportation mobility on COVID-19 becomes more robust at the medium to upper quantiles of transportation mobility and lower to upper quantiles of COVID-19. However, this effect is weaker at intermediate quantiles of COVD-19 and gets more potent at the higher equidistant quantiles of COVID-19. Overall, the results document an overall adverse effect of COVID-19 on transportation, while transport mobility has an overall declining negative effect on the pandemic spread in Spain. These results are in line with the findings of Aloi et al. [43], who reported that traveling and mobility patterns play a vital role in declining transmission.

In **Italy**, the association between COVID-19 and transportation mobility is negative. An adverse effect of COVID-19 on transportation mobility is found in the region syndicated by the top quantiles (0.80–0.95) of COVID-19 and lower, upper and higher quantiles (0.2–0.95) of transportation mobility. The COVID-19 has a strong positive impact on transportation mobility at medium quantiles of COVID-19 (0.50–0.80) and the highest quantiles of transportation mobility (i.e., 0.80–0.95). On the other side, the impact of transportation mobility on COVID-19 is significantly shortened and negative in the formed region of lower quantiles of transportation mobility and lower to higher quantiles of COVID-19. Though, the weaker effect is translated at intermediate quantiles of COVD-19 and then becomes stronger from medium to upper quantiles of COVID-19. A strong positive effect of a COVID-19 pandemic can also be traced at the most upper quantiles of transportation mobility and from lower to upper quantiles for COVID-19. From the findings, we conclude that COVID-19 has a negative impact on transportation mobility. In contrast, transportation mobility has a rising positive effect on COVID-19. In short, we may conclude that COVID-19 leads to a reduction in transportation, while areas with excessive levels of transportation mobility increase the number of pandemic cases.

These results match the findings of Cartenì et al. [22], who reported that mobility habits are highly correlated with COVID-19 cases.

In the case of **France**, the effect of CIVID-19 on transportation mobility is predominantly negative with the declining trend. A little weaker effect is found at higher quantiles of COVID-19 (0.85–0.95) as well as upper quantiles of transportation mobility (0.85–0.95). A positive impact of COVID-19 on transportation mobility is originated at the upper quantiles of COVID-19 (0.80–0.95) and across all the quantiles of transportation mobility (0.05–0.95). On the other side, the impact of transportation mobility on COVID-19 is very condensed and negative at lower to medium quantiles of transportation mobility and low to higher quantiles of COVID-19. However, this effect becomes moderate at intermediate quantiles of COVID-19 and becomes stronger from medium to upper quantiles of COVID-19. A strong positive effect is observed from medium to upper quantiles of transportation mobility and lower to upper quantiles of COVID-19. From the findings, we conclude that COVID-19 has a negative impact on transportation mobility. In comparison, transportation mobility has a rising positive effect on COVID-19. The results of France are consistent with the prior study of Alandijany et al. [44], who documents that control measures like suspension of flights, limited mobility are dampening the massive spread of the infection in GCC countries.

The effect of COVID-19 on transportation mobility in **Germany** is negative and the same as it is in Italy. An adverse impact of COVID-19 on transportation mobility is found at top quantiles (0.80–0.95) of COVID-19 and with the medium to highest quantiles (i.e., 0.40–0.95) of transportation mobility. A positive effect of COVID-19 on transportation mobility is originated at medium quantiles of COVID-19 (0.60–0.80) and the highest quantiles of transportation mobility (0.80–0.95). In both COVID-19 and transportation mobility, an adverse effect of COVID-19 on transportation mobility is also observed at the most upper quantiles. In contrast, the impact of transportation mobility on COVID-19 is very truncated and negative at lower quantiles of transportation mobility and lower to higher quantiles of COVID-19. Though, this effect is weaker at intermediate quantiles of COVD-19 and then develops a strong impact from medium to upper quantiles of COVID-19. A robust positive outcome is also observed at the most upper quantiles (0.70−0.95) of transportation mobility and lower to higher quantiles (0.30−0.95) for COVID-19. Overall, COVID-19 has a negative impact on transportation mobility. In comparison, transportation mobility has a rising positive effect on COVID-19. In short, we may conclude that COVID-19 leads to an overall reduction in transportation mobility. In contrast, Germany's higher level of mobility is expected to increase the number of infected cases. These findings are congruent to Borkowski et al. [45] for Poland and Yabe et al. [46] for Tokyo, Japan.

In **Canada**, the effect of COVID-19 on transportation mobility is negative for all the combinations of quantiles of COVID-19 and transportation mobility. A positive impact of COVID-19 on transportation mobility is originated at medium to upper quantiles of COVID-19 (0.70–0.95) and across all the quantiles of transportation mobility (0.05–0.95). A weak effect of COVID-19 on transportation mobility is observed at the highest quantiles (0.80–0.95) of COVID-19. In contrast, the shortened and negative effect of transportation mobility on COVID-19 is found at lower quantiles of transport (i.e., 0.05–0.30) and the lower to highest quantiles of COVID-19 (0.20–0.95). Moreover, the effect of transportation mobility on COVID-19 becomes substantial at the medium to higher quantiles of transportation mobility and lower to upper quantiles of COVID-19. Though, this effect is weaker at intermediate quantiles (0.50−0.60) of COVD-19 and then becomes stronger at the upper quantiles of COVID-19. From the findings, we conclude that COVID-19 has a negative impact on transportation mobility. In comparison, transportation mobility has a rising positive effect on COVID-19. In short, we may conclude that COVID-19 hinders transportation over the selected time period; excessive levels of transportation mobility in specific spatial and temporal areas have escalated the pandemic spread. These results match with the findings of Xiong et al. [47], who reported that human mobility and COVID-19 infections are highly correlated and positive.

In **Belgium**, the association between COVID-19 and transportation mobility is positive in lower quantiles. An adverse effect of COVID-19 on transportation mobility is found in the region that syndicates the highest quantiles (0.80–0.95) of COVID-19 with the medium to highest quantiles (0.45–0.95) of transportation mobility. COVID-19 positively affects transportation mobility in the formed region of lower to upper quantiles of COVID-19 (0.05–0.95) and the highest quantiles of transportation mobility (0.70–0.95). In contrast, the impact of transportation mobility on COVID-19 is significantly shortened and negative at lower quantiles of transportation mobility (0.05−0.40) and lower to higher quantiles (0.05−0.95) of COVID-19. However, at intermediate quantiles of COVD-19, this effect is weaker and drives strong with rising magnitude from medium to upper quantiles of COVID-19. The transport mobility has a positive and significant effect in the joined region of medium to upper quantiles of transportation mobility and lower to upper quantiles for COVID-19. From the results, we conclude that COVID-19 has a negative impact on transportation mobility. In comparison, transportation mobility has a rising positive effect on COVID-19. In this context, we may conclude that COVID-19 reduces transportation flows. These results align with the findings of Noland [48], which confirm that the effectiveness of mobility reductions plays a vibrant role in the effective reproduction of COVID-19 cases.

Checking the validity of the QQ method

To validate the results of the QQR method in the previous section, the average estimates of slope coefficients associated with quantile-on-quantile regression should be almost equivalent to those of conventional quantile regression analysis. In this regard, we can compare the approximate quantile regression parameters with the parameters of τ-averaged QQR to test the validity. Fig. 4 claims to offer a comparative appraisal of QQR with the QR method, endorses prior findings, and tracks similar patterns. The graphs of sample countries show that the average values of the QQR coefficients are roughly identical to those of the QR coefficients and switch with each other. Such findings affirm our prior QQR results in Fig. 3. The graphical evidence in Fig. 4 contends that the results of both the quantile regression model and QQR estimates follow approximately similar trends, which further confirm the validity of QQR approach.

Results of quantile Granger causality in mean

The methodology section applies the quantile Granger causality test between COVID-19 and transportation mobility using Eq. (13). Table 3 displays the quantile Granger causality paths and includes the D_T test p-values for log parameters. The p-values of all 19 quantile grids (i.e. 0.05, 0.10, 0.20 . . .,0.85, 0.90, 0.95) were recorded for all 10 selected countries. D_T values vindicate that bi-directional causality exists between COVID-19 and transportation mobility at a 5% level of significance in almost all quantiles in the case of all sample countries except France. The USA, Brazil, the UK, and Canada have bi-directional (feedback relationship) causality between COVID-19 and transportation mobility in their upper quantiles (0.75−0.90). Similar bi-directional causality results have also been found in the middle quantiles (0.50−0.55) for the USA, Brazil, Mexico, and Germany.

On the other hand, France has unidirectional causality that extends from COVID-19 to transportation mobility in all condi-

Table 3
Results of quantile Granger causality.

Country/quantiles	0.5–0.95	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
USA																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.80	0.37	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.09	0.82	**0.05**	**0.01**	**0.01**	**0.03**	**0.04**	**0.01**
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	0.06	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.06	**0.03**	0.11	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**
Brazil																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.70	0.64	0.10	0.12	0.51	0.12	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.19	0.10	**0.03**	**0.02**	**0.01**	**0.01**	**0.01**	**0.01**
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.07	0.31	0.28	**0.02**	**0.02**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.43
Mexico																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.37	0.56	0.48	0.21	**0.05**	0.37	**0.02**	**0.01**	0.07	**0.01**	0.50	0.64	0.32	0.44	0.48	0.08	0.24	0.30	**0.01**
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.71	**0.02**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.02**
UK																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.10**	0.56	0.56	0.04	**0.01**	**0.01**	**0.04**	0.08	0.12	0.13	0.43	0.45	0.34	0.20	**0.01**	**0.01**	**0.01**	**0.02**	**0.01**	0.11
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	0.16	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.06	**0.02**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.06
Spain																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.95	0.81	0.56	**0.03**	0.05	**0.01**	**0.01**	0.06	0.09	0.03	0.44	0.05	0.29	0.22	**0.01**	0.30	**0.01**	**0.01**	0.14
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	**0.02**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.30	**0.03**	0.11	0.11	**0.02**	0.16	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**
Italy																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.29	0.21	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.33	0.89	0.12	0.16	**0.01**	**0.03**	0.12	**0.01**	0.16	0.72
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.06	0.36	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**
France																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.68	0.71	0.08	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.64	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.78
$\Delta COV19_t \rightarrow \Delta TRMB$	0.20	0.30	**0.01**	0.07	0.22	0.37	0.42	0.39	0.16	0.92	0.70	0.21	0.29	0.49	0.28	0.60	0.15	**0.05**	0.09	0.29
Germany																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.98	0.82	0.15	**0.05**	**0.01**	**0.02**	**0.01**	**0.03**	0.06	**0.04**	**0.02**	0.36	0.50	**0.05**	**0.03**	0.06	0.08	**0.04**	0.27
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.22	0.34	0.21	**0.03**	0.29	0.30	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**
Canada																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.32	**0.01**	0.14	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.08	0.68	0.17	**0.03**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.48	0.06	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.06
Belgium																				
$\Delta TRMB_t \longleftarrow \Delta COV19$	**0.01**	0.36	0.84	0.15	**0.05**	**0.03**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.02**	**0.03**	0.16	**0.01**	**0.01**	**0.01**	**0.05**	**0.01**	0.36
$\Delta COV19_t \rightarrow \Delta TRMB$	**0.01**	0.11	**0.04**	**0.01**	**0.01**	**0.03**	0.09	0.16	0.24	0.42	0.64	0.08	**0.05**	**0.01**	**0.01**	**0.01**	0.08	**0.01**	0.56	0.31

Note: Table shows the p-values subsampling. $\Delta TRMB_t$ is the log difference of transport mobility index and $\Delta COV19$ is the log difference of daily COVID19 cases. $I_t^{\Delta TRMB_t} = 1$ $\left(I_t^{\Delta COV19} = 1\right)$ is the number of lag selection of dependent variable. The size of subsample is b = 35 of total sample N = 131 observations. The bold values indicate the rejection of null hypothesis of non-Granger-causality at 5% level of significance.

tional distribution quantiles. These causality results indicate that COVID-19 and transportation mobility are strongly linked in almost all countries across all quantiles. COVID-19 not only causes transportation mobility but also affects COVID-19 at most of the middle to upper quantiles. Our findings are supported by previous studies such as Kartal et al. [49] in the case of Turkey and Zhu et al. [50] for Latin American countries. They reported that various types of mobility have a causality on the number of COVID -19 patients and deaths. These findings further confirm our mainstream findings of QQR methodology and its validity analysis.

Discussion of the results

Our QQR results indicate heterogeneous results about the linkage between COVID-19 and transportation mobility across space and time due to the varying natures of countries' mobility patterns, infection rates, and spatial variations. The majority of sample countries such as the USA, UK, Spain, Italy, Canada, France, Germany and Belgium have found a positive linkage between COVID-19 and transportation mobility. This positive linkage is more pronounced in higher quantiles of both variables. This positive linkage between COVID-19 and transportation mobility indicates that excessive transportation mobility in these countries increases COVID-19 transmissibility [47,51].

The analysis results indicate that COVID-19 has an overall negative impact on transportation mobility and vice versa. These findings indicate that COVID-19 has adversely affected transportation mobility in the ten selected countries by reducing the volume of driving, transit, and walking modes due to social distancing and quarantining to mitigate this exceptionally growing rate pandemic spread over the globe. The increasing number of infection cases in these countries has seized these countries' social and economic activities. Governments are compelled to reduce the excessive and undue concentration of social and traffic mobility. Such drastic measures are necessary to control the ever-increasing number of COVID-19 cases. The other side of the picture also indicates the adverse impacts of transport mobility on pandemic spread when transportation is temporally and spatially condensed and excessive in certain regions. This mainly happened, for instance, in Italy, Spain, and the USA, which overlooked the severity of the pandemic spread during the early phase of its development. The lack of systematic and effective policy to regulate transportation mobility in these countries led to the dramatic spread of COVID-19, which caused thousands of deaths in these top affected countries. The empirical findings of the current study offer helpful insight into the strong linkage between the spread of COVID-19 and the effection of the transportation mechanism. Our results indicate that COVID-19 cases are lower when transport mobility is lower, while the higher level of transportation has caused more pandemic cases. These results are generally consistent with the prior studies [50,52,53]. However, the reduction in transport mobility in lock-down areas has adversely affected the socio-economic activities and slowed down the transmission intensity, which would benefit the societies in the short run.

Our quantile Granger causality results validate the previous findings of QQR and verify mainly bidirectional causal linkage between COVID-19 and transportation mobility in almost all quantiles for all sample countries except France. However, France has unidirectional causality that extends from COVID-19 to transportation mobility in all conditional distribution quantiles. The results

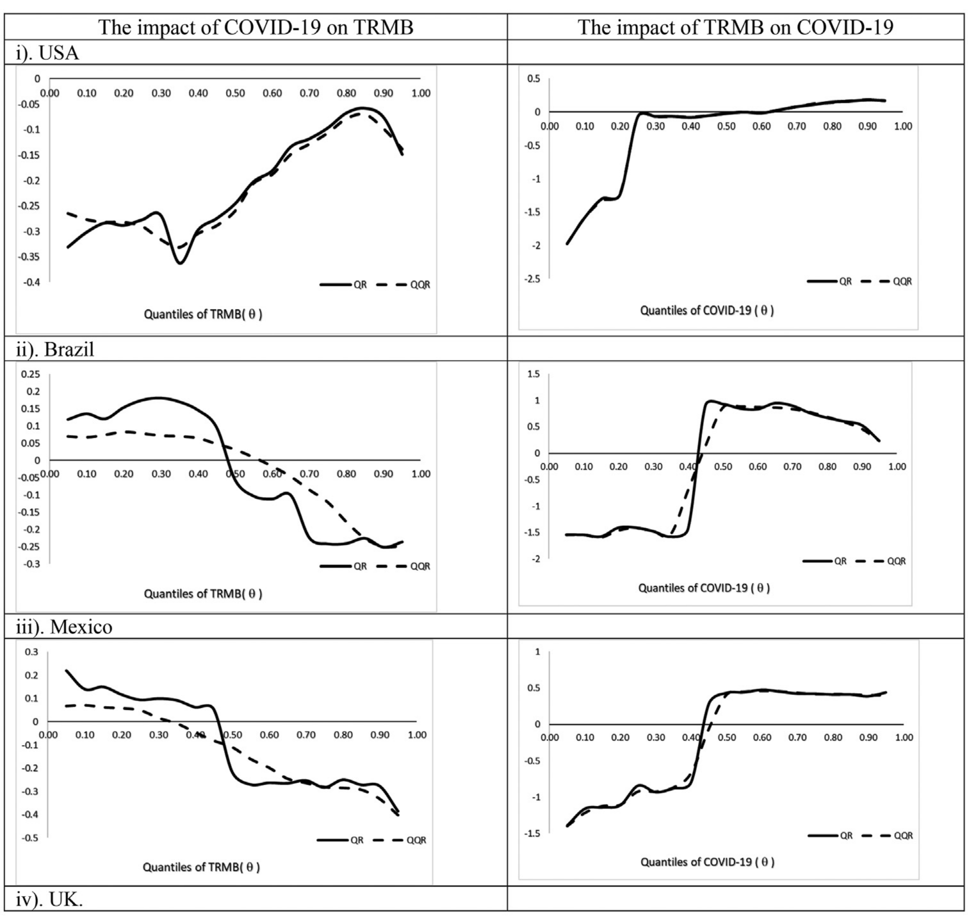

Fig. 4. Comparison between quantile on quantile and quantile regression.

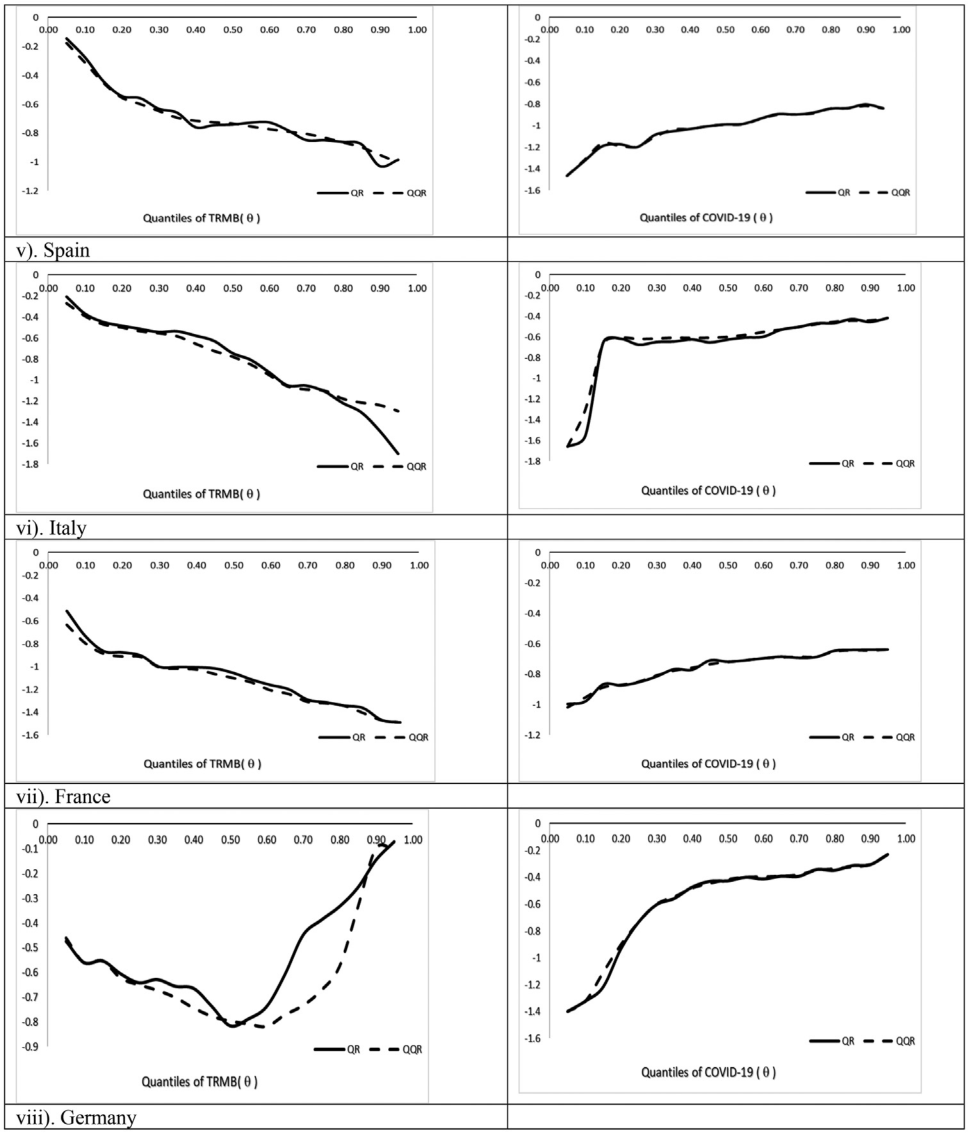

Fig. 4. (*Continued*)

of quantile Granger causality also act as a robustness measure to our mainstream findings of QQR approach. The bidirectional causal nexus has also been pragmatic in previous studies [54,55].

We conclude a robust connection between mobility measurements and transmissibility for ten selected countries that have experienced or have yet to experience substantial active SARS-CoV-2 (COVID-19) transmission, supporting the population-wide social distancing interventions for controlling the epidemic. In most countries, we have found encouraging evidence of the recent dampening of transmission and mobility linkage, suggesting that alternative control techniques have been successfully instigated and transmission has decreased significantly.

Conclusion and policy implications

This current study empirically examined the asymmetric linkage between COVID-19 and transportation mobility for ten selected countries by applying an advanced and robust QQR method to the daily data from 1st March 2020 to 15th July 2020. This study used the latest and advanced methodology suggested by Sim and Zhou [24]. It gives a more comprehensive and accurate picture of cross-dependence between COVID-19 and transportation mobility than conventional econometric models such as ordinary least squares or quantile regression because it captures the effect of quantiles of COVID-19 on the quantiles of transportation mobility. Also, the asymmetric impact of transportation mobility on COVID-19 induces non-linearity over different quantiles. The present study also employs non-linear quantile Granger causality proposed by Troster et al. [25] to investigate the causal linkage between COVID-19 and transportation mobility to validate the prior findings of the QQR approach.

The empirical findings present divergent and heterogeneous outcomes across several syndicated regions generated by the quantiles of COVID-19 and transportation mobility, signifying the asymmetric effects anticipated by QQR. The empirical results indicate that linkages between transportation mobility and COVID-19 are highly correlated for all countries. However, there is extensive deviation throughout countries and also across all quantiles of COVID-19 and transportation mobility in every country. The findings show that the linkage between transportation mobility and COVID-19 is positive at upper quantiles for the USA, UK, Spain, Italy, Canada, France, Germany and Belgium. An adverse effect of transportation mobility on COVID-19 is observed for upper quantiles in Mexico, Italy, Germany, and Spain. On the other side, the impact of

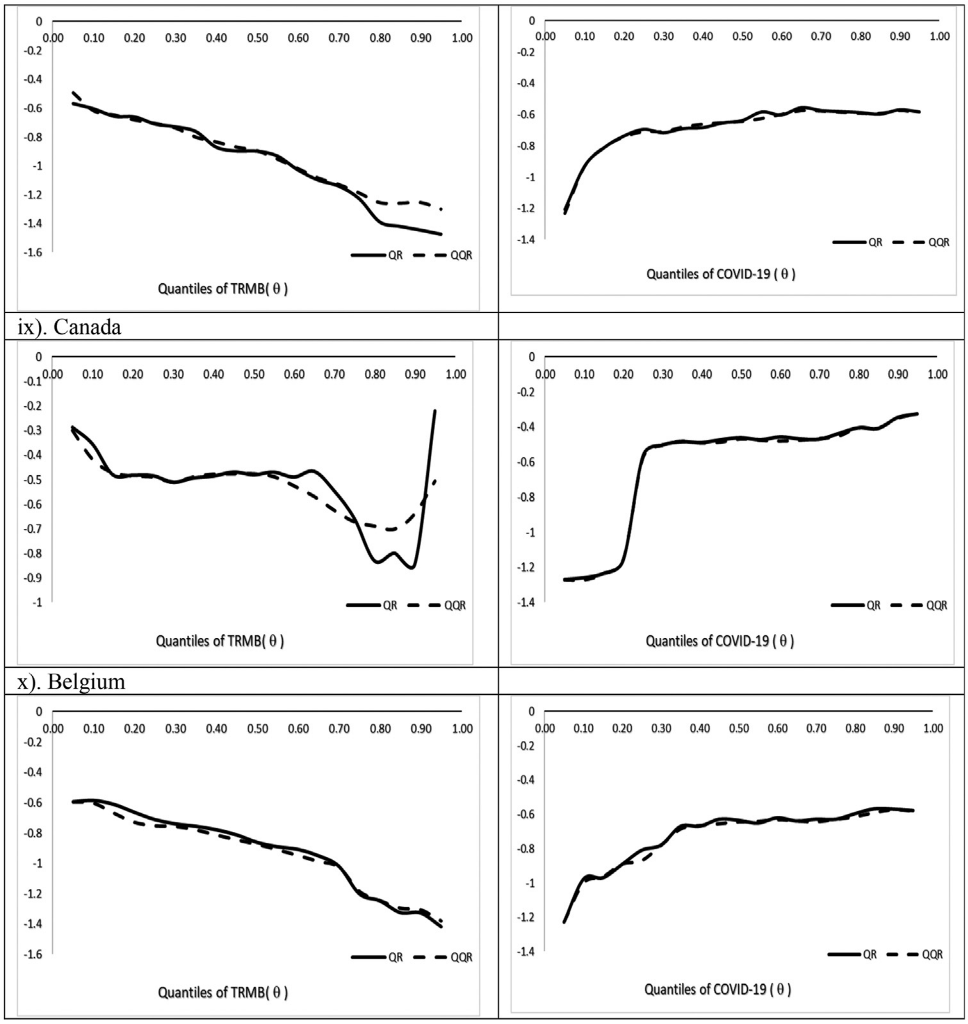

Fig. 4. (*Continued*)

transportation mobility on COVID-19 is very condensed and negative at lower quantiles of transportation mobility and low to high quantiles of COVID-19 for all selected countries. Though, this effect is weaker at intermediate quantiles of COVD-19 and then becomes more potent at the upper quantiles of COVID- 19. Overall, these findings reveal that transportation mobility has a declining negative effect on COVID-19, (but in a few cases like the USA, Brazil, this relation is positive in medium and upper quantiles). In contrast, COVID-19 has an overall negative impact on transportation mobility by reducing the volume of driving, transit, and walking modes due to social distancing and quarantining to mitigate this exceptionally growing rate of pandemic spread over the globe.

The quantile Granger causality estimates indicate that bidirectional causality and feedback relation exists between COVID-19 and transportation mobility at a 5% significance level in almost all quantiles for all sample countries except France. These quantile causality results indicate that COVID-19 and transportation mobility are strongly linked in almost all countries across all quantiles. In contrast, France has found unidirectional causality that extends from COVID-19 to transportation mobility in all conditional distribution quantiles. In short, COVID-19 causes transportation mobility, but transportation mobility also affects COVID-19 at most of the middle to upper quantiles.

Our empirical work has important policy implications for respective governments, policy-makers, international health organizations, crisis management departments, environmental agencies, and the public for devising appropriate strategies to control COVID-19 and develop efficient transport mechanisms for scheduled and safely planned deliveries of goods during such crises. This study strenuously advocates social distancing or isolation as an impactful way to reduce the spread of COVID-19. Until a COVID-19 vaccine is widely accessible, social distancing would endure being one of the primary measures to encounter the disease transmission, and these findings should help in the future to promote more proactive policymaking around social distancing in the world. The issue of transportation mobility should be handled wisely to a trade-off between the benefits of a complete lock-down scenario and flexible socio-economic activities. In such a panic period, scheduled and limited social and business mobility is encouraged for only essential and prioritized work for the early phase of pandemic spread. Moreover, the transport mechanism and modes should be highly integrated with the latest virus detection technology and health inspection spots. Such pandemic crises could be mitigated at the early phase of development in the future. This research is limited to quantifying the relationship between transportation mobility patterns and COVID-19 cases. Therefore, this study fails to account for the role of other mitigating potential factors (e.g., wearing facial masks and handwashing) as they might have contributed to the decline in the case growth rate. Since this novel methodology allows us to study the asymmetric linkage between two variables, more empirical work is still needed to figure out how to balance the expected positive effect on public health with the detrimental impact on freedom of mobility, the economy, and society at large.

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Competing interests

None declared.

Ethical approval

Not required.

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