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Digital financial inclusion, the belt and road initiative, and the Paris agreement: Impacts on energy transition grid costs

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ABSTRACT

We investigate how digital financial inclusion, the Belt and Road Initiative, and the Paris Agreement influence the energy transition grid cost. We propose two new Kendall and Spearman wavelet cross-quantile correlation methods and utilize data from June 1, 2018, to July 31, 2024. Our findings indicate that digital financial inclusion, the Paris Agreement, and artificial intelligence significantly reduce grid costs in the short and long run. Additionally, the Belt and Road Initiative has substantial potential to decrease grid costs, particularly during bullish market conditions in the long run. Conversely, GCOVOL significantly increases grid costs, especially in the long run.

1. Introduction

Recent research highlights that energy transition (SDG 7) is vital for sustainable development and addressing environmental challenges like climate change and resource depletion (United Nations, 2024). The pace of global sustainable development depends on how swiftly this transition occurs. However, a key barrier is the high cost of transforming power grids—known as energy transition grid cost (ETGC)—to integrate renewable energy sources (Financial Times, 2023). This includes expenses for adapting the grid to transport renewable electricity. Analysts at BloombergNEF (2023) estimate that the global cable network needs to double by 2050, requiring $21 trillion in investment (Financial Times, 2023; OilPrice, 2023). These costs and the complexities of integrating renewables slow the global transition. This discussion highlights the critical role of ETGC as a bottleneck in the energy transition. However, existing research has yet to thoroughly explore this area. This study aims to analyze the key drivers of ETGC to address its challenges in the current era of advanced technologies and inform policy-making. We focus on the roles of digital financial inclusion (DFI), the Belt and Road Initiative (BRI), and the Paris Agreement (PA) in reducing ETGC. For example, DFI can improve access to financing for SMEs in the renewable energy sector (Lu et al., 2023; Li et al., 2023), supporting investment in decentralized energy solutions. The BRI promotes infrastructure investment across countries (Cao et al., 2024; Lin and Bega, 2021), potentially reducing the costs of developing cross-border energy grids. Additionally, the Paris Agreement's carbon reduction commitments encourage policies and incentives (Yang et al., 2024), promoting smart grid investments. Together, these initiatives can lower ETGC by enhancing financial access, fostering cooperation, and driving green energy adoption.

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Similarly, advanced technologies like artificial intelligence (AI) are making significant contributions across all sectors globally (Zhang et al., 2024), including the energy sector. Further, AI can optimize energy grid operations by improving demand forecasting, balancing renewable supply, and enhancing grid efficiency, leading to potential cost savings (B. Wang et al., 2024). However, global economic shocks—such as the 2008 financial crisis, COVID-19, and the Ukraine-Russia war (URW)—have created uncertainty and driven high inflation rates (Dogah et al., 2024; Lee and Lee, 2024), which can slow the energy transition by raising grid costs. In summary, this discussion highlights critical research gaps. For example, previous studies mainly focus on the key drivers of energy transition. Wang et al. (2024) identify digital finance as a vital driver of energy transition since digital finance makes it easier the access to financial services by offering fast (Zhou et al., 2023; Tian et al., 2022; Yue et al., 2022), convenient, and secure online platforms (Ye and Yue, 2024; Xu et al., 2024; Hao et al., 2023) for transactions, lending, and investments.

Also, Owolabi et al. (2024) identify the role of PA in determining the financial flows for environmental quality, affecting the energy transition. However, the pertinent academic literature has not examined how digital financial inclusion (DFI) could address the challenges of ETGC, a key barrier to the energy transition. Additionally, the roles of the Belt and Road Initiative (BRI) and the Paris Agreement (PA) in reducing ETGC have not been sufficiently explored. Furthermore, the potential of AI to assist in this scenario, especially amid global economic shocks, remains unclear. To address these gaps, this study asks, "What is the nexus between digital financial inclusion, the BRI, the Paris Agreement, and energy transition grid cost?"

Our study addresses this query and advances the literature in several ways. First, it uniquely considers digital financial inclusion (DFI) as a key driver of ETGC, analyzing its impact due to its strong connection to the energy transition. Second, it examines the roles of two major global initiatives, the Belt and Road Initiative (BRI) and the Paris Agreement, in reducing ETGC and promoting sustainable energy. Third, it explores the influence of artificial intelligence (AI) on ETGC, expanding on recent research regarding AI's role in energy transitions. Fourth, it analyzes how DFI, BRI, and the Paris Agreement affect ETGC amidst recent economic shocks, offering insights into their interactions during uncertainty. Lastly, the study introduces three novel econometric methods—Kendall Wavelet Cross-Quantile Correlation, Spearman Wavelet Cross-Quantile Correlation, and partial Wavelet Cross-Quantile Correlation —to assess these impacts over different time horizons, providing a valuable methodological contribution.

2. Method and data

For empirical analysis, this study introduces a new method, the Wavelet Cross-Quantile Correlation (WCQC) approach, to investigate the frequency cross-quantile relationship between two series. The previous techniques like wavelet correlation (Whitcher et al., 2000), quantile correlation (G. Li et al., 2015), and wavelet quantile correlation (Kumar and Padakandla, 2022) perform analysis using the MODWT of Percival and Walden (2000) and the quantiles of one series. Further, cross-quantilogram (Han et al., 2016) performs the analysis, using the quantiles of both series but without deploying the MODWT. However, none of the developed correlation methods combine wavelet with the quantiles of both time series. In order to fill this gap, we introduce the WCQC in this paper using the wavelet idea and quantiles of both two-time series to investigate the frequency cross-quantile relationship between two variables. Notably, the WCQC allows us to analyze the relationship between the quantiles of two-time series across the periods.

In the application process, the WCQC first standardizes both series under consideration, as in Baruník Kley (2019). Second, the WCQC decomposes standardized series via the MODWT from 1 to the maximum depth (scale) of the decomposition (ϕ) .[1] Third, it estimates the conditional quantile series of the decomposed series using the quantile estimation technique of T.-H. Li (2022). Last, the WCQC estimates correlation coefficients for each quantile pair. The WCQC coefficients can be estimated between two variables as follows:

$$wcqc(A,B) = \mathbb{C}\left(\phi A_t^\tau, \phi B_t^\tau\right) \tag{1}$$

where ϕA_t^τ and ϕB_t^τ represent τ-th quantile of the ϕ-th decomposition series of A_t and B_t, respectively, and $\mathbb{C}$ implies correlation.

The WCQC is a nonlinear approach in nature as it considers both the frequency and quantile-dependent relationship between two variables. Therefore, the Kendall and Spearman correlation methods are suitable for the WCQC as they do not assume linearity and normality as the Pearson correlation method and are more robust to nonlinear relationships. The WCQC coefficients can be estimated via the Kendall and Spearman correlation methods as follows:

$$kwcqc(A,B) = \frac{2(CP - DCP)}{n(n-1)} = \frac{2}{n(n-1)}\sum_{t<i} s\left(\phi A_i^\tau - \phi A_t^\tau\right) s\left(\phi B_i^\tau - \phi B_t^\tau\right) \tag{2}$$

$$swcqc(A,B) = 1 - \frac{6\sum\left(R\phi A_t^\tau - R\phi B_t^\tau\right)^2}{n(n^2-1)} \; or \; \frac{\mathbb{C}\left(R\phi A_t^\tau, R\phi B_t^\tau\right)}{\sigma_{R\phi A^\tau}\sigma_{R\phi B_t^\tau}} \tag{3}$$

Where *kwcqc* and *swcqc* indicate the Kendall and Spearman WCQC correlations, respectively. Although the novel WCQC and Partial WCQC[2] methods proposed in this study overcome the shortcomings of prior pertinent methods, they exhibit some limitations, such as not considering lag-lead and time-varying relationships.

[1] It is important to note that the maximum depth (scale) of the decomposition (ϕ) is estimated as $log_2(n) - 3$, where n is the total number (i.e., length) of the sample period, as recommended by Polanco-Martínez (2023).

[2] Kindly see Appendix A for the details of Partial WCQC method.

2.1. Data and preliminary analysis

For analysis, we take the data for DFI (proxied by Alternative Finance Index), the BRI (proxied by BRI index by Chishti et al. 2024), the Paris Agreement (proxied Net Zero 2050 Paris-Aligned ESG Index), AI (proxied by Global Artificial Intelligence Enablers Index), GCOVOL (proxied by COVOL index by Engle and Campos-Martins 2023 to measure the economic shocks). Further, we develop an energy transition grid cost index to measure the ETGC. To do so, we utilize the data of two series, such as smart grids and electricity transmission & distribution infrastructure indexes and take their average to make the index, following Khalfaoui et al. (2023). The data for all series are retrieved from S&P Dow Jones Indices (https://www.spglobal.com/spdji/en/), except for BRI and GCOVOL indices. The range of the data is from 01 to 06–2018 to 31–07–2024, as per the availability of data conditions, and we take log differences from the series. The trends of the opted series are visualized in Fig. 1. The statistical description and BDS test's outcome are reported in Tables 1 and 2.

3. Results and discussion

For a comprehensive analysis, we decompose all the standardized series under consideration using the maximum decomposition depth (scale) of 7, estimated as $log_2(1599) - 3$. Therefore, we obtain 8 decomposed series as d1, d2, d3, d4, d5, d6, d7, and s7 for each data series. These decomposed series represent 2–4, 4–8, 8–16, 16–32, 32–64, 64–128, 128–256, and above 256 days, respectively. By following Gök et al. (2022), we sum d1, d2, d3, and d4 for the short-run representing 2 to 32 days. For the long run, we sum d5, d6, d7, and s7 representing over 32 days. Further, we assume that 0.05 to 0.3, 0.4 to 0.6, and 0.7 to 0.95 quantiles represent the bearish, normal, and bullish market conditions.

The Kendall WCQC method-based results are reported in Fig. 2. It is important to note that if there is a positive QC between the independent and dependent series, it implies that ETGC is decreasing due to the independent series; otherwise, it is increasing. Looking at the case of DFI, we observe that, in the short-run (SR), there is a positive quantile correlation (QC) between DFI and ETGC across most market conditions. This correlation tends to be more significant in the long run (LR), so ETGC demonstrates the positive QC across most market conditions. This implies that DFI plays a vital role in decreasing the grid cost of green energy from SR to LR across most market situations. Further, DFI's influence on the fall in grid cost is more pronounced in the LR. These findings are unique and confirm the significant role of DFI.

Like DFI, we noticed that PA also showed a positive QC with ETGC across most of the market conditions in the SR. Interestingly, this positive correlation becomes more significant across bearish, normal, and bullish market situations in LR. The results determine that PA significantly reduces the grid cost, specifically in the LR. Moving toward the QC between BRI and ETGC, no significant correlation is witnessed in the SR. However, in the LR, ETGC has a negative association with the BRI during bearish and normal conditions, implying the BRI caused an increase in the grid cost during the aforementioned market situations. The bullish market situation of ETGC exhibits a positive correlation with the normal and bullish markets of BRI. This implies that, at the beginning of LR, grid cost tends to rise; however, in the long run (during the stability period), the grid cost tends to fall on account of BRI. The findings suggest that BRI seem to support the sustainable energy future by cutting down its grid cost, as Ullah et al. (2023) report that BRI supports green energy production.

In the case of GCOVOL, it is noticed that, in the SR, ETGC shows no significant QC with GCOVOL with the exception of a few quantiles with the mixed correlation. In the LR, a significant negative QC is witnessed across most of the market conditions. It implies that global economic shocks significantly cause an increase in the grid cost, most probably due to increasing the prices by creating uncertainties Zhang et al. (2023). Finally, the case of AI confirms a significant QC during SR and LR across most of the market situations. Logically, AI can reduce energy transition grid costs by optimizing maintenance, forecasting demand, and managing renewable integration. It enhances grid flexibility through decentralized resources, smart storage, and efficient EV load management, as Shoaei et al. (2024) argued.

3.1. Further analysis

As for the first robustness check, the Spearman WCQC method-based results are depicted in Fig. 3. The Spearman WCQC-based results support the main findings. For the sensitivity analysis, we use the smart grids index (SMTG) as it reflects technological advancements central to cost reduction, operational efficiency, and infrastructure modernization (SandP Global, 2024), all of which are integral to the ETGC index. The findings in Fig. 4 indicate the significant correlation between the opted series and SMTG, supporting the main findings. Subsequently, the analysis for COVID-19 to assess the influence of the global pandemic. To this end, the study develops and employs the novel partial Kendall WCQC method and chooses the period of COVID-19 from 01 to 10–2019 to onward as suggested by Naeem et al. (2021). The results are visualized in Fig. 5, which considers the partial effects of GCOVOL in capturing the effects of COVID-19. The findings exhibit that the significance level of correlation between the series becomes weak, signifying the influence of COVID-19. This outcome is in line with the results by Yu and Xiao (2023), Chancharat & Sinlapates (2023), and Huang et al. (2023).

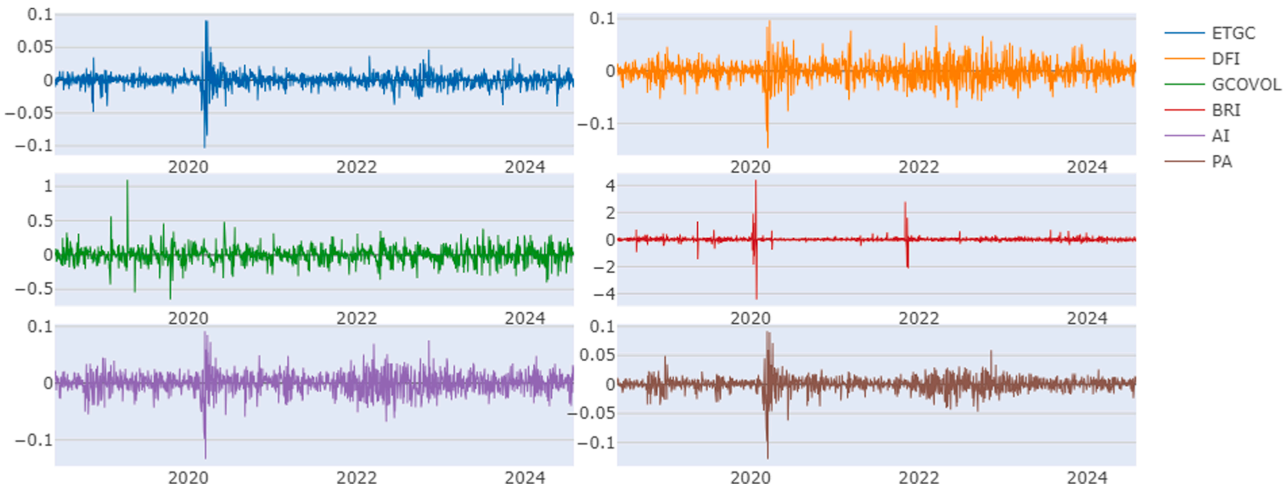

Fig. 1. Trends in the opted series.

Table 1
Descriptive statistics.

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
ETGC	7.27E-05	0.000755	0.091319	−0.10348	0.011303	−0.42278	18.41532	15,879.87
DFI	−0.00024	0	0.096978	−0.14691	0.020555	−0.28758	6.440224	810.5566
BRI	−0.00063	−0.00795	4.407736	−4.42635	0.245713	0.314635	156.2273	1,564,289
PA	0.000491	0.000526	0.091729	−0.12836	0.012961	−0.67957	16.7485	12,716.61
AI	0.00059	0.001185	0.091689	−0.13366	0.017925	−0.42178	7.053597	1142.169
GCOVOL	−0.00026	0	1.095228	−0.64721	0.113132	0.416493	10.7671	4065.572

Table 2
BDS test.

Dimensions	ETGC	DFI	GF	PA	AI	GCOVOL
2nd	8.415***	8.566***	11.315***	10.929***	6.504***	5.346***
3rd	11.275***	10.584***	13.563***	14.679***	9.524***	6.771***
4th	12.661***	11.903***	15.079***	17.466***	11.528***	8.409***
5th	13.967***	12.924***	16.592***	19.882***	13.179***	9.598***
6th	15.405***	14.198***	18.450***	22.548***	14.945***	10.697***

4. Conclusion

We analyze the role of DFI, BRI, PA, AI and GCOVOL in determining the energy transition grid cost across various time horizons, deploying the new Kendall and Spearman wavelet cross-quantile correlation (WCQC) approach. The findings reveal that DFI plays a vital role in supporting the sustainable energy future by reducing grid costs across most market conditions in the short and long run. Similarly, PA and AI encourage access to green energy by disrupting the ETGC in both periods. The case of BRI exhibits no significant link with the grid cost. However, the long-run findings demonstrate the BRI's positive link with grid cost across bearish and bullish market conditions and the negative link when the market condition is bullish. GCOVOL significantly escalated the grid cost across most market situations in the long run. We also performed the analysis for the period of COVID-19 while applying the partial WCQC method. The outcomes show that the nexus between DFI, PA, BRI, AI, and ETGC has to endure significant influence due to COVID-19.

Our findings suggest that global policymakers should encourage the DFI and invest in artificial intelligence technologies to reduce the ETGC for a sustainable energy future. Also, the global authorities induce the global nations to be active members of global initiatives like the Paris Agreement and the BRI, as these initiatives have significant potential to reduce grid costs. Finally, global policymakers should take serious steps to disrupt the detrimental effects of global economic shocks on the energy transition market.

CRediT authorship contribution statement

Muhammad Zubair Chishti: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xiqiang Xia:** Writing – review & editing, Validation, Supervision. **Anna Min Du:** Writing – review & editing, Writing – original draft, Validation, Resources, Investigation. **Oktay Özkan:** Writing – original draft, Investigation, Formal analysis.

Appendix A: Partial Wavelet Cross-Quantile Correlation

To examine how the frequency cross-quantile relationship between two variables changes by controlling the third variable, we also introduce Partial Wavelet Cross-Quantile Correlation (PWCQC). The PWCQC can be estimated as follows:

$$pwcqc(A,B) = wcqc(A,B) - E(C) - E(I) \tag{A1}$$

where $E(C)$ and $E(I)$ imply the effect of third variable and its interaction on the frequency cross-quantile correlation between two variables, respectively. $E(C)$ and $E(I)$ can be calculated as below:

$$E(C) = wcqc(A,B) - \frac{\mathbb{C}(\phi A_t^\tau, \phi B_t^\tau) - \mathbb{C}(\phi A_t^\tau, \phi C_t^\tau)\mathbb{C}(\phi B_t^\tau, \phi C_t^\tau)}{\sqrt{\left(1-\mathbb{C}^2(\phi A_t^\tau, \phi C_t^\tau)\right)\left(1-\mathbb{C}^2(\phi B_t^\tau, \phi C_t^\tau)\right)}} \tag{A2}$$

$$E(I) = wcqc(A,B) - \frac{\mathbb{C}(\phi A_t^\tau, \phi B_t^\tau) - \mathbb{C}(\phi A_t^\tau, \phi I_t^\tau)\mathbb{C}(\phi B_t^\tau, \phi I_t^\tau)}{\sqrt{\left(1-\mathbb{C}^2(\phi A_t^\tau, \phi I_t^\tau)\right)\left(1-\mathbb{C}^2(\phi B_t^\tau, \phi I_t^\tau)\right)}} \tag{A3}$$

The PWCQC coefficients can also be estimated using the Kendall and Spearman correlation methods, such as WCQC.

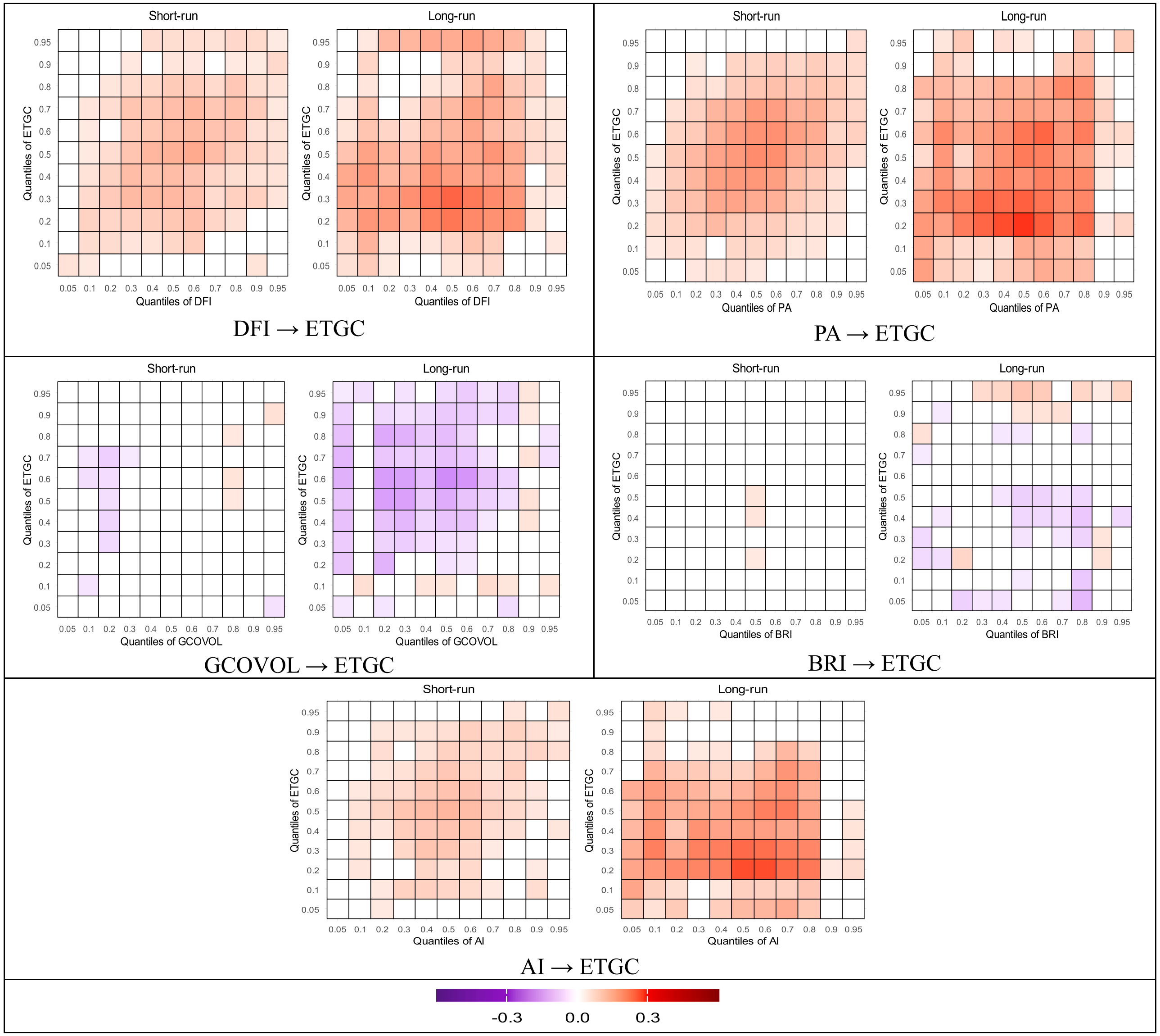

Fig. 2. Kendall WCQC method-based results.

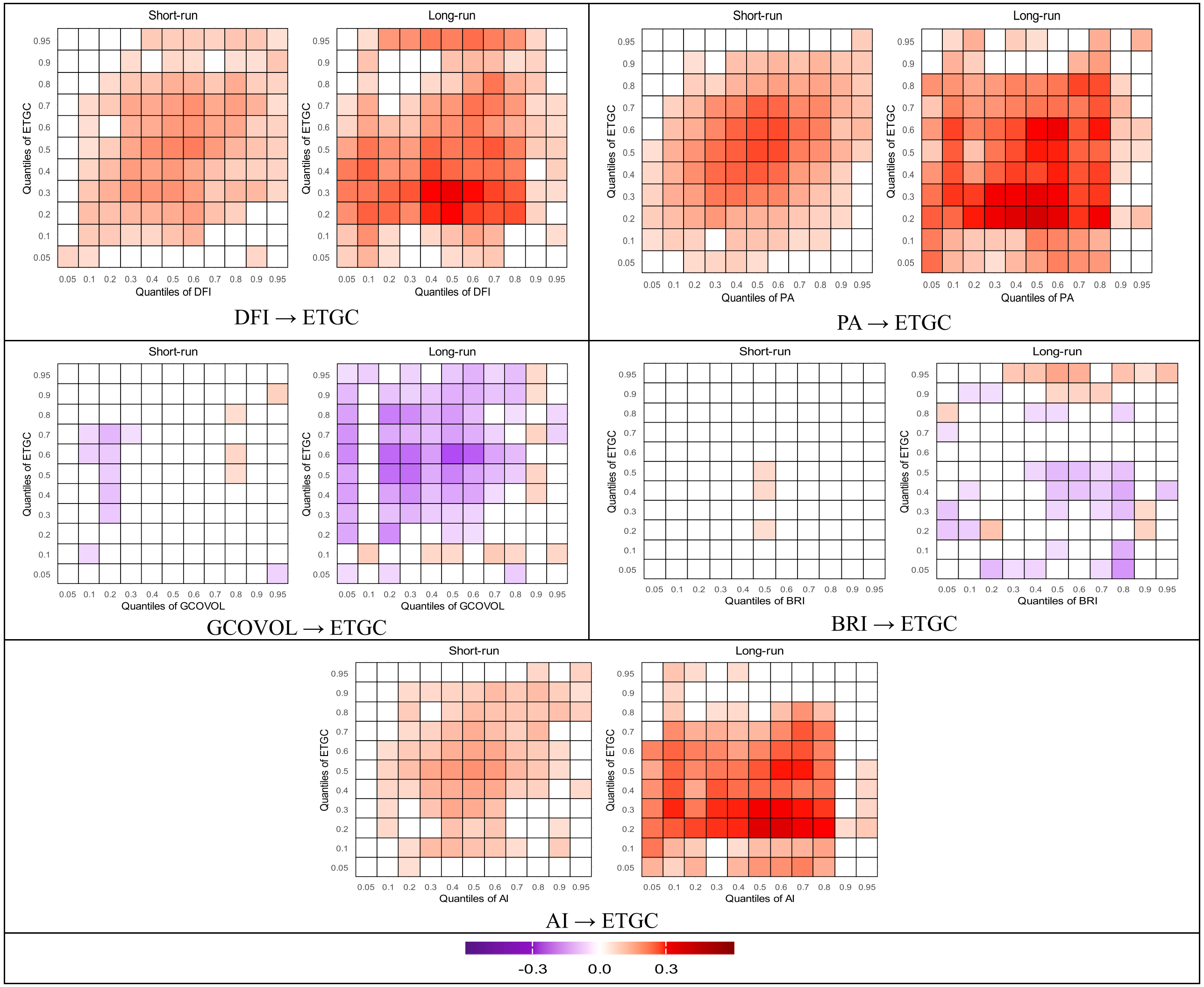

Fig. 3. Spearman WCQC method-based results.

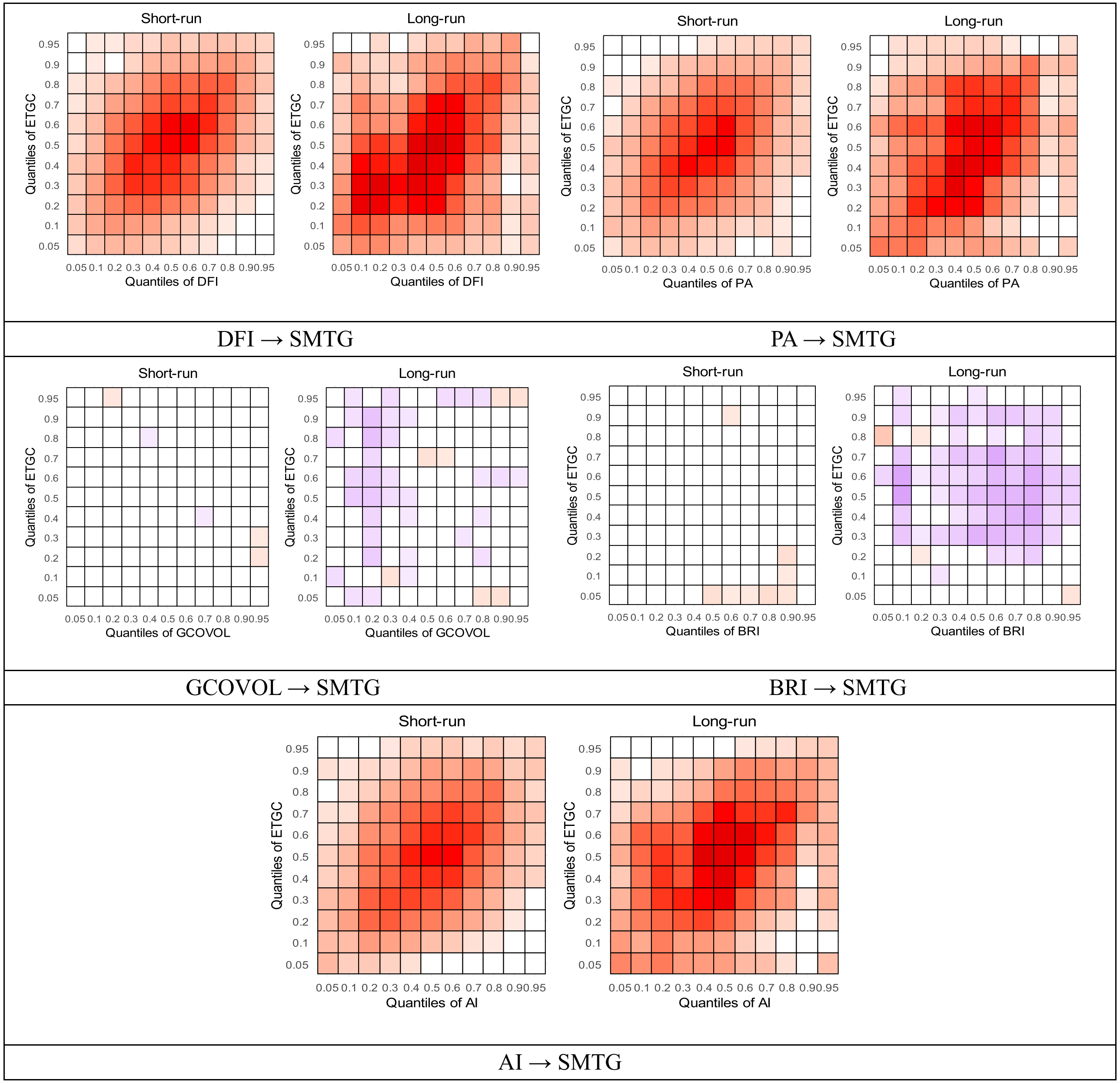

Fig. 4. Kendall WCQC method-based sensitivity analysis.

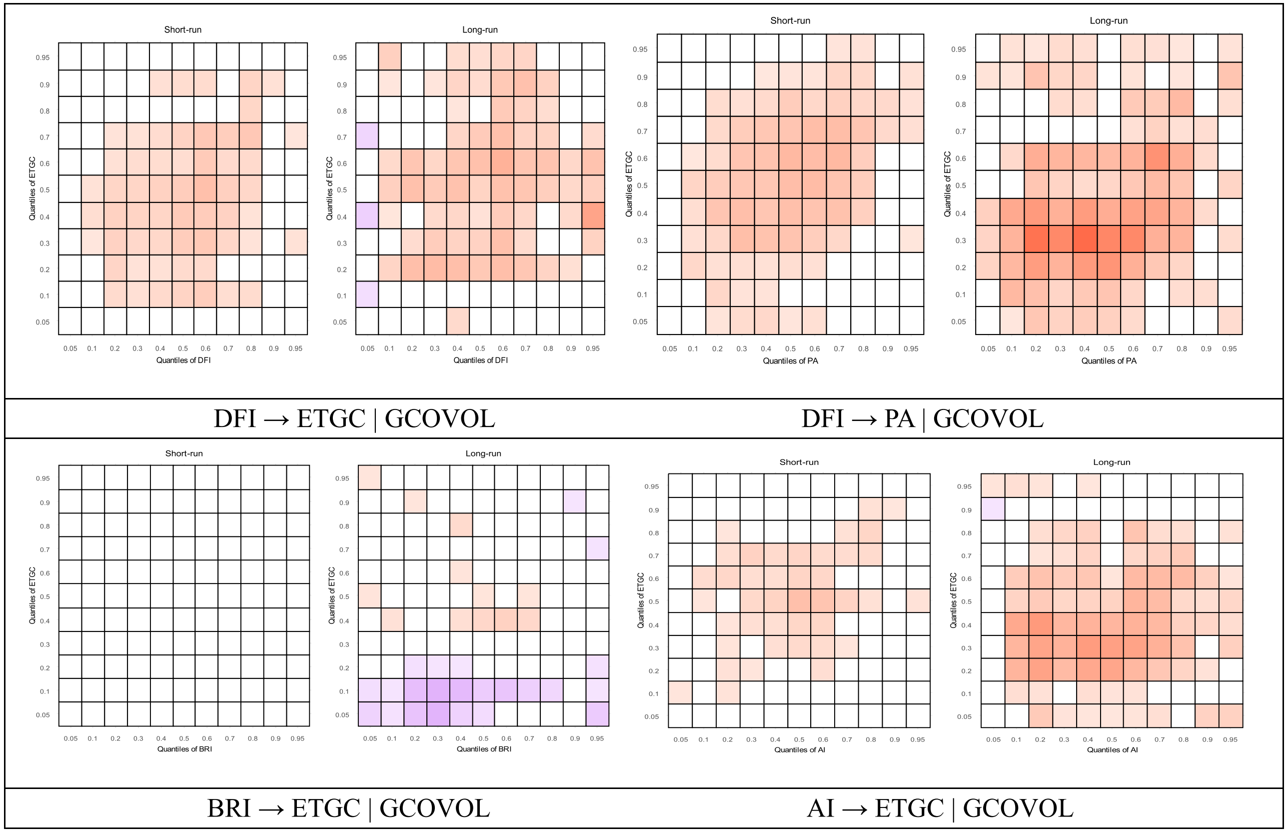

Fig. 5. Partial Kendall WCQC method-based results for COVID-19 period.

Data availability

Data will be made available on request.

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