The Effect of Green Bonds on Climate Risk Amid Economic and Environmental policy uncertainties

Kamel Si Mohammed

Faculty of Economics and Management, University of Ain Temouchent, Algeria

kamel.simohammed@univ-temouchent.edu.dz

Vanessa Serret (corresponding author)

Université de Lorraine, CEREFIGE, F-57000 Metz, France

vanessa.serret@univ-lorraine.fr

Christian Urom

CRECC, Paris School of Business, France

The Effect of Green Bonds on Climate Risk amid Economic and Environmental Policy Uncertainties

Abstract

This study investigates the impact of green bonds on climate risk indices, specifically considering the Economic Policy Uncertainty (EPU) Index and the climate summit index. The analysis covers the time frame from November 28, 2008, to August 31, 2022, using multivariate quantile-on-quantile regression (MQQR) and quantile-on-quantile regression (QQR) approaches. The main findings indicate that green bonds have significant potential in addressing climate risk despite economic and environmental policy uncertainty. This suggests the need for an incentive framework to support the development of green bonds in the American market to facilitate progress towards achieving Sustainable Development Goal 13 concerning climate action.

Keywords: Green bonds; climate risks; economic policy uncertainty; multivariate quantiles-on-quantile methods

JEL classifications: G12; G14; Q43

1. Introduction

A recent US Energy Information Administration (EIA, 2023) report stated that the United States will emit 4,971 million metric tons of energy-related CO2 in 2023 because of the implementation of regulatory reforms and the enhancement of green finance. The United States re-entered the Paris Agreement following a change of administration in 2021 and set a new goal to reduce greenhouse gas emissions by 50–52% from 2005 levels by 2030.[1] Green bonds are a crucial instrument in sustainable finance, representing a tangible and practical approach to addressing climate-related risks (Al Mamun et al., 2022). They facilitate the direct allocation of financial resources to initiatives that promote environmental sustainability, resulting in measurable decreases in carbon emissions and the promotion of renewable energy solutions (Chopra and Mehta, 2023). The increasing interest in eco-centric investments indicates a strong market demand and has prompted private and public sectors to enhance their dedication to green-centric initiatives.

The present study examines the influence of green bonds on climate risk by considering the effect of the Economic Policy Uncertainty (EPU) Index and climate summits from 2008 to 2022. This research paper outlines three distinct scholarly contributions. First, the study aims to contribute to the limited literature on the impact of green bonds and climate risk by investigating the influence of green bonds on climate risk. (Wang et al., 2022) examined the impact of green bond issuance on corporate climate risk perceptions from 2011 to 2020. They found that for most firms, the level of awareness about climate risks increased following the issuance of green bonds. (Sartzetakis, 2020) explored the potential of green bonds in facilitating the transition towards a low-carbon economy and proposed potential strategies aimed at addressing existing challenges to promoting the expansion of the green bond market. Second, this study represents the first attempt at integrating economic policy considerations and uncertainties surrounding climate summits. These components help in explaining economic and environmental effects, allowing investors, policymakers, and businesses to create informed strategies that address the complexities involved. Third, the methodological design of this study represents a significant contribution. (Sim and Zhou, 2015) created an approach to bivariate analysis regression that employed quantile-on-quantile

[1] https://www.whitehouse.gov/climate/

regression (QQR), a methodological design signifying a considerable advancement. The present investigation improves on established methodologies by incorporating the novel technique of multivariate quantitative qualitative reasoning (MQQR) developed by (Sinha et al., 2023).

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the dataset and methodology. Section 4 presents and discusses the results and provides hedging implications. Section 5 concludes by underlining the need to develop the green bond market.

1.1. Data harvesting mechanism

This study investigates the impact of green bonds on climate risk by considering the EPU index and the climate summit effect. To do this, we used the EPU index of the St. Louis Federal Reserve Bank. In order to characterize the climate summit, the Climate Summit Index (CSI) developed by (Ardia et al., 2022) was utilized to assess changes in climate summits, government programmes, and the climate carbon tax. The data used in this analysis were obtained from the Media Climate Change Concerns[2] (2023) database. We incorporated the daily prices of S&P green bonds, specifically, the SPGF index, as a benchmark for evaluating the performance of green finance. The price data were obtained from the Refinitiv Eikon database.

Then climate change indices (CCI) is developed by (Ardia et al., 2022). The analysis covered the time frame from November 28, 2008, to August 31, 2022. This period encompasses various significant events, including the subprime crisis, the European debt crisis, the COVID-19 pandemic, Brexit, the Russian conflict with Ukraine, COP14 in Poland, COP Copenhagen, the signing of the Paris Agreement in 2015, ultimately culminating in COP27 in Egypt.

1.2 Model estimation with the M-QQR approach

The QQR method (Sim and Zhou, 2015) is widely used in academic research to evaluate the dynamic and nonlinear influence of quantile-dependent variables on quantile-independent variables across different market conditions. (Sinha et al., 2023) developed the multivariate QQR method, which incorporates the moderating effects of additional exogenous variables via interactions and may encounter the omitted variable bias of

[2] https://sentometrics-research.com/download/mccc/

bivariate QQR, which was created by (Sim and Zhou, 2015). These models effectively address challenges such as heteroskedasticity, skewness, serial correlation, and structural breaks (Sim and Zhou, 2015). Moreover, both the QQR and QR methodologies offer a mechanism for examining the association between, and assessing the presence of, symmetrical impacts among variables. The mathematical equation for the MQQR is estimated as follows:

$$MCCC = \beta^{\theta}\,(GBI) + \sum_n \beta^{\theta}(x_t)\ + \sum_n \gamma^{\theta}(GBI * x_t) + \epsilon^{\theta}.(1)$$

Where GBI is the green bond index, MCCC is a climate risk; x_t represent the matrix of n exogenous variables; ϵ and θ are the error term and quantile, respectively.

2. Main findings and discussion

2.1 Summary statistics and pairwise correlations

This section discusses the preliminary results of the analysis of the descriptive statistics, as shown in **Table 1**. Besides the basic summary statistics, we also tested for the ARCH-LM, non-normality, skewness, and kurtosis of the selected series. All data values had significant variance, not far from their respective mean values, and had modest variations, indicating that the chances of outliers in the data series were not limited. The selected series were positive and significantly skewed, except for the GBI, which was statically significant, albeit with a negative value. The kurtosis coefficients of the series show excess kurtosis, as the number exceeded three, stipulating the deviation of these series from the normal distribution. All series passed the Jarque-Bera test and failed the normality test – evident from the probability values – indicating that their periods did not follow a normal distribution. The Jarque-Bera test statistics also revealed that the quantile-based framework was the most suitable approach for tackling nonlinearity in the data series. Finally, the ACRH ARCH-LM tests confirmed the non-normality distribution test and non-homoskedasticity in all four variables.

<Insert Table 1>

2.1. Window moving, dynamic conditional correlation and diagnostic tests

In order to make progress towards the development of quantile-based estimations, it is crucial to determine whether any time-varying correlations were present within the series. To achieve this objective, we calculated the moving-window correlation and the dynamic conditional correlation regarding the relationship between green bonds and climate risk. The results are depicted in Figures 1 and 2. The analysis of the correlation between these two variables over a 30-month rolling window revealed a varying correlation in both direction and magnitude. To mitigate the issue of heteroskedasticity, we employed the dynamic conditional correlation technique. The results from this approach were consistent with the rolling-window correlation analysis, which demonstrated periodic variations in both the direction and strength of the correlation. The complex correlation structure observed implied the presence of a potential quantile dependence between the two series.

Moreover, the correlation between these series potentially depended on external factors shaping the nature of the relationship. At the start of our inquiry, we initiated preliminary diagnostic examinations, the findings of which are presented in Tables 2–4. The results of our exogeneity test shed light on the independence of our chosen moderators, that is, the independence of the climate summit and EPU indices from the hypothesized relationship. Table 3 provides additional evidence to support the soundness of our parameter selections by comparing the results obtained from the least angle regression method. Building on the positive diagnostic findings, we further embarked on an empirical investigation. The subsequent sections provide a detailed explanation of the results obtained from the QQR and MQQR tests.

<Insert Figure 1>

<Insert Figure 2>

<Insert Table 2>

<Insert Table 3>

2.3. QQR findings

The results of the model, which were obtained using the QQR approach, are illustrated in Figure 4. The slope coefficients of the QQR approach in the diagram represent the impact of the τth quantile of green bonds on the λth quantile of climate risk. A consistent and notable positive climate risk can be observed in the lower quantiles of the GBI, which ranges from 0.05 to 0.35. The observed circumstances can be attributed to a lack of financial resources, which hinders the adequate mitigation of the risks associated with climate change. Additionally, there has been a significant increase in project financing. The current escalation is characterized by a prevalence of warm shades in the yellow and green spectrum, fluctuating between five and 20% in the visual representation.

Nevertheless, as we moved towards the higher percentiles of the GBI, there was a noticeable decline in the inclination towards climate risk. The decrease in emissions was attributed to the substantial assistance offered by green finance, increased green innovation, R&D, and green low-carbon projects. The provision of financial support significantly aided in implementing environmentally friendly initiatives, reducing climate-related risks. The prevalence of blue tones often symbolized this outcome. This difference in the timing of costs and benefits explains why contentious discussions over climate risk and green bond investments have typically driven climate summits.

<Insert Figure 3>

2.4. MQQR findings

In our research, we used the novel multivariate QQR technique to investigate the complexities of specific interactions. One notable finding is the significant positive increase in the influence of green bonds on climate risk. Compared to the EPU index and the CSI, this was especially pronounced across various quantiles of the GBI (ranging from 0.05 to 0.95) and at the lower and medium levels of MCCC and the EPU index. Compared to the bivariate impact of the GBI on MCCC, the QQR findings show that when moderated by the EPU index rather than the CSI, this reduced effect was more discernible. When climate risk (MCCC) and other exogenous variables registered at high quantiles, this trend appeared to reverse.

Differently put, green bonds appeared less effective at mitigating the negative consequences of climate risk during times of heightened uncertainty or peak risks. Their effectiveness in mitigating climate risk, particularly in the climate summit context, declined at the lower (0.3th to 0.4th) and extreme upper (0.9th to 0.95th) quantiles. This dynamic was obvious in terms of the impact of the GBI on MCCC within the context of the climate summits. This pronounced effect was most noticeable in upper market conditions when EPU was present.

<Insert Figure 4>

<Insert Figure 5>

These findings not only foster a sense of responsibility and increased awareness about climate risks following the use of green bonds, as demonstrated by (Sartzetakis, 2020), but also have the potential to mitigate the economic obstacles to environmentally friendly endeavours by reducing climate risk expenses. The increasing prevalence of green finance suggests a significant implication: green bonds facilitate economic transformations and shape policy frameworks in favour of a more environmentally friendly trajectory (Tolliver et al., 2019). Additionally, this outcome suggests the need for a policy framework to support the United States in achieving the objectives outlined in Sustainable Development Goal 13 pertaining to climate action (Bhutta et al., 2022). Within the wider context of EPU, green bonds symbolize stability, providing both domestic and international investors with insight into a country's commitment to environmental concerns. By directing investments towards resilient sectors, green bonds serve as more than just economic instruments but, rather, strategic defences and a safe haven against anticipated economic disruptions (Chopra and Mehta, 2023).

3. Conclusion and policy implications

This study sought to examine the influence of green bonds on climate risk indices, focusing specifically on the EPU index and the CSI, using the MQQR and QQR methodologies. The research findings indicate that green bonds have significant potential in climate risk mitigation. The allocation of revenue derived from them holds significant potential in mitigating regressive consequences, wherein the adverse effects on people with lower incomes outweigh those experienced by the more affluent.

This article offers some insights for investors and policymakers. A practical incentive framework could include several key elements to enhance the green bond market. First, governments can offer guarantees to reduce the financial risk associated with green bonds, thus attracting more investors, including those traditionally more cautious. Moreover, it is necessary to establish clear and internationally recognized criteria for what constitutes a 'green bond' so as to increase investor confidence (e.g. investors with lower incomes). This involves creating standards for using investment funds, monitoring, and communication on environmental impacts as well as imposing stringent reporting requirements and transparency on money flows.

Consequently, to stimulate the green bond market, it is fundamental to promote these products by educating investors about green finance. Regarding the organizational efficiency of markets, it could be interesting to develop specific trading platforms for green bonds and ensure easy access for investors to facilitate transactions and increase liquidity in this market. There is also a need to consider appropriate mechanisms to assist smaller-sized companies in accessing the green bond market, which runs the risk of being dominated by large entities.

By integrating these elements, policy makers can foster a better environment for issuing and subscribing to green bonds, thereby enhancing sustainable finance and combating climate change.

References

Al Mamun, M., Boubaker, S., Nguyen, D.K., 2022. Green finance and decarbonization: Evidence from around the world. Finance Research Letters 46, 102807. https://doi.org/10.1016/j.frl.2022.102807

Ardia, D., Bluteau, K., Boudt, K., Inghelbrecht, K., 2022. Climate Change Concerns and the Performance of Green vs. Brown Stocks. Management Science. https://doi.org/10.1287/mnsc.2022.4636

Bhutta, U.S., Tariq, A., Farrukh, M., Raza, A., Iqbal, M.K., 2022. Green bonds for sustainable development: Review of literature on development and impact of green bonds. Technological Forecasting and Social Change 175, 121378. https://doi.org/10.1016/j.techfore.2021.121378

Chopra, M., Mehta, C., 2023. Going green: Do green bonds act as a hedge and safe haven for stock sector risk? Finance Research Letters 51, 103357. https://doi.org/10.1016/j.frl.2022.103357

Sartzetakis, E.S., 2020. Green bonds as an instrument to finance low carbon transition. Economic Change and Restructuring 1–34. https://doi.org/10.1007/s10644-020-09266-9

Sim, N., Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. Journal of Banking and Finance 55, 1–8. https://doi.org/10.1016/j.jbankfin.2015.01.013

Sinha, A., Ghosh, V., Hussain, N., Khuong, D., Das, N., 2023. Green financing of renewable energy generation : Capturing the role of exogenous moderation for ensuring sustainable development. Energy Economics 126, 107021. https://doi.org/10.1016/j.eneco.2023.107021

Tolliver, C., Keeley, A.R., Managi, S., 2019. Green bonds for the Paris agreement and sustainable development goals. Environmental Research Letters 14. https://doi.org/10.1088/1748-9326/ab1118

Wang, C.W., Wu, Y.C., Hsieh, H.Y., Huang, P.H., Lin, M.C., 2022. Does green bond issuance have an impact on climate risk concerns? Energy Economics 111, 106066. https://doi.org/10.1016/j.eneco.2022.106066

Table 1: descriptive statistique

	GBI	**MCCC**	**CSI**	**EPU**
Mean	107.205	0.751	0.385	123.957
Variance	52.194	0.178	0.125	7297.979
Skewness	-0.223***	0.948***	2.808***	2.358***
	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	3.059***	4.359***	16.213***	11.379***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	30.192***	813.570***	30828.036***	13827.452***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH-LM	3543.309	479.338	1123.109	1756.989
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3589	3589	3589	3589

Table 2: Exogeneity results

	Wu-Husman ST	pvalue	Durbain &Wu-Husman	pvalue
CSI	213.3	0.00	199.6	0.00
EPU	2.55e	0.00	1.49e	0.00

Table 3: Least angle regression

step	Mallow's Cp	R-square	Action

1	3738.8	0.00	+
2	577.7	0.433	+CSI
3	2.2	0.512	+GBI
4	4*	0.512	+EPU

*The optimum values selection of the minimum M-Cp based on the lasso Algorithm

Figure 1. M-W correlation (30 days W-rolling)

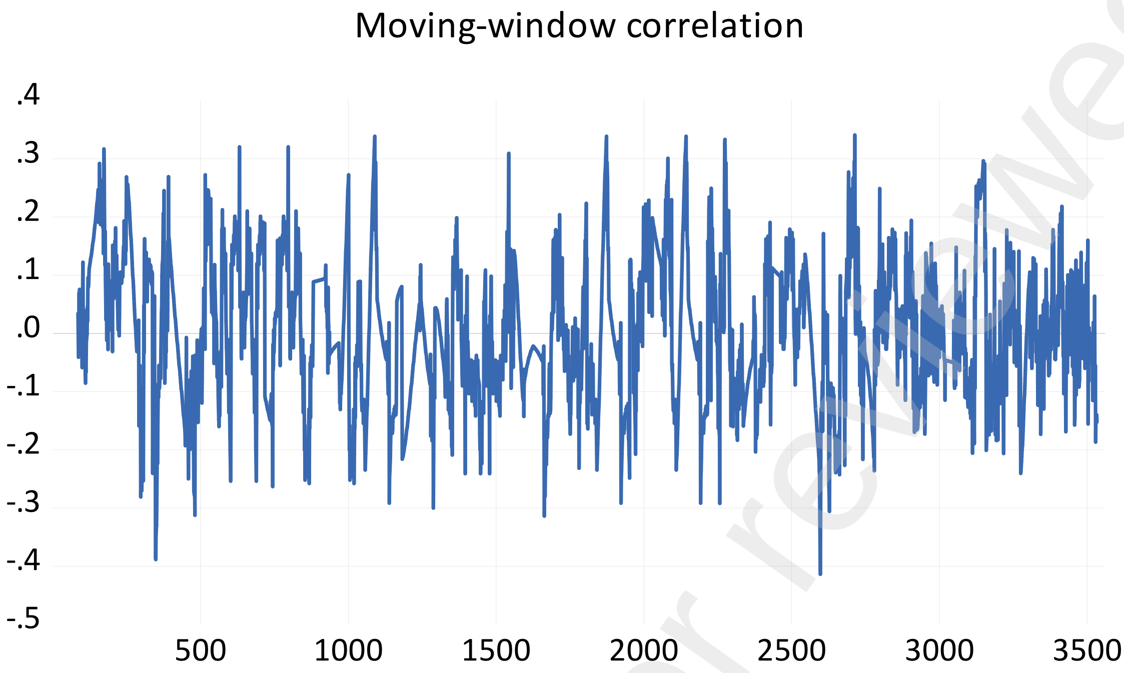

Figure 2. DCC between GBI and MCCC

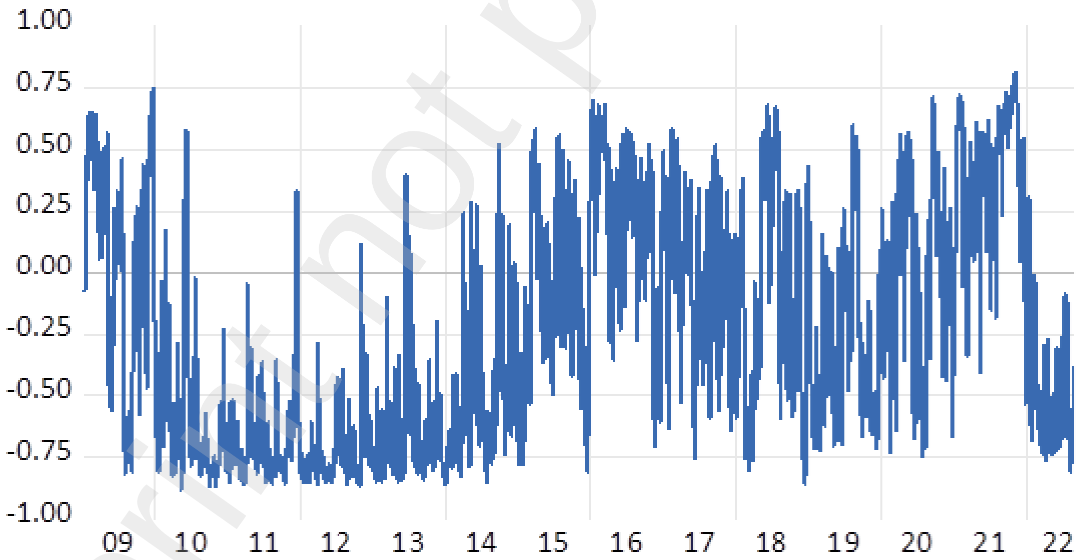

Figure 3 QQR results between MCCC and GBI

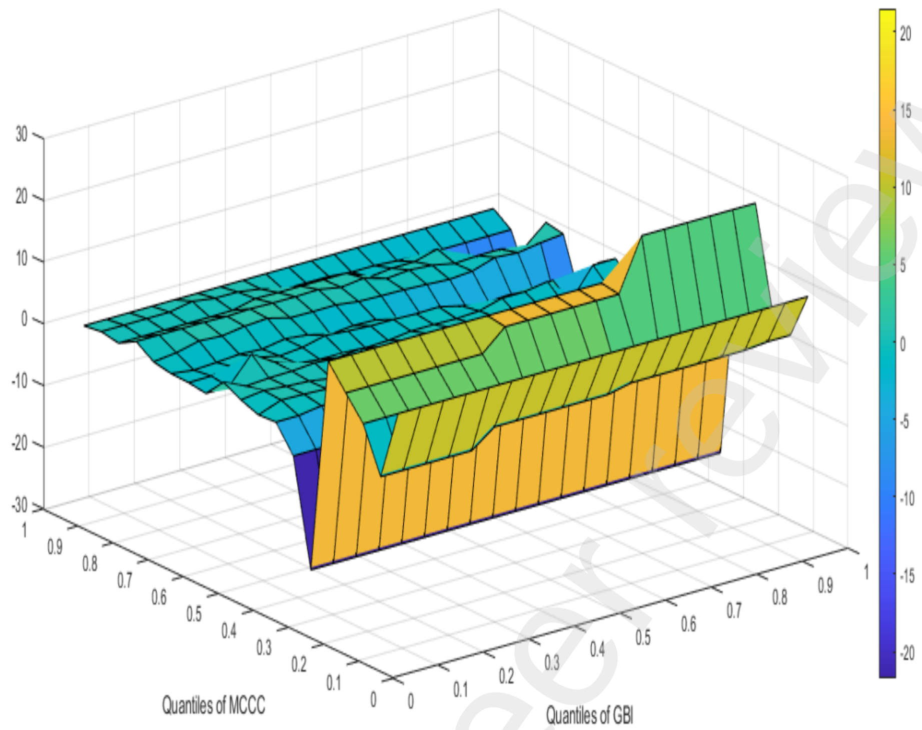

Figure 4 MQQR results in the presence of CSI

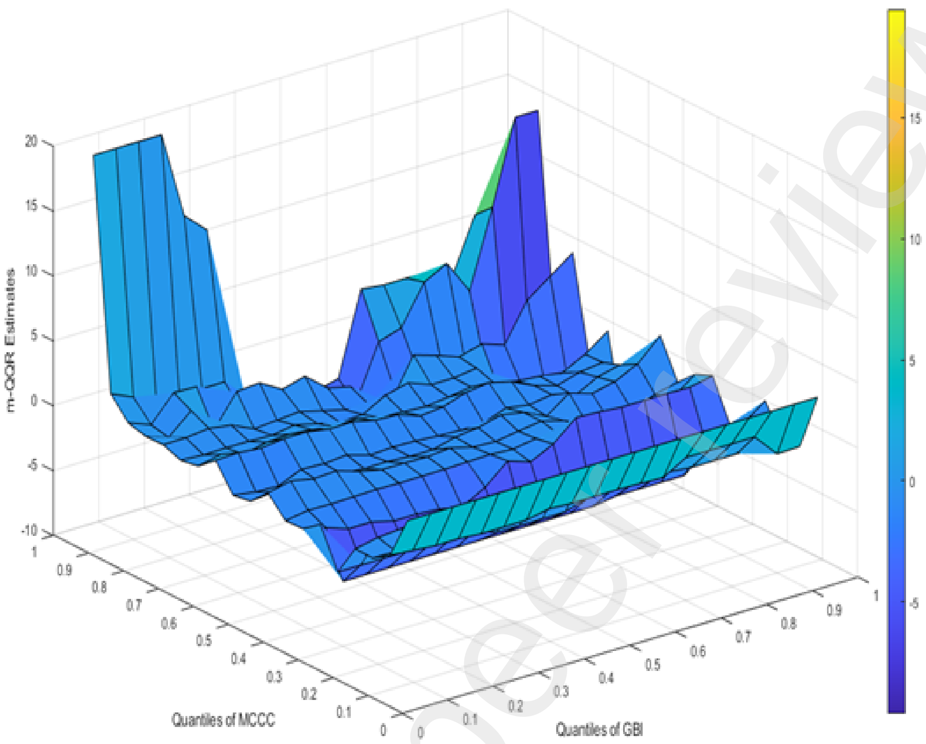

Figure 5 MQQR results in the presence of EPU