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# **Economic policy uncertainty, macroeconomic shocks, and systemic risk: Evidence from India**

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# **Course: Financial Risk Analysis and Management (FIN F414)**

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# **i. Highlights**

Economic policy uncertainty (EPU) plays a significant role in influencing systemic risk (SYS), particularly during periods of crisis. This study identifies both immediate and delayed dependencies between EPU and SYS, underlining the necessity of stable policymaking in times of uncertainty. Macroeconomic shocks (MS) demonstrate a delayed effect on SYS, offering policymakers a strategic window to address potential risks. The analysis reveals a limited direct relationship between MS and EPU, suggesting that macroeconomic shocks have less influence on policy uncertainty. Utilizing Cross-Quantilogram (CQ) analysis, the study captures the directional dependencies across different quantiles, providing insights into both extreme and moderate events. SYS and EPU show an immediate interdependency, while the relationship between SYS and MS peaks with a delay, specifically at lag 10 for extreme events. The findings emphasize the importance of adaptive and proactive policymaking to address systemic risks in an evolving economic landscape.

**ii. Abstract**

This research explores the interactions between economic policy uncertainty (EPU), macroeconomic shocks (MS), and systemic risk (SYS) in India, using data from January 2000 to June 2024. The study employs Cross-Quantilogram (CQ) analysis, a sophisticated statistical method, to assess the dependencies between these variables across different quantiles and time lags. The results reveal that EPU has an immediate impact on SYS, while the effects of MS on SYS are delayed, offering policymakers a potential window to implement risk-mitigating strategies. Notably, the study finds that EPU plays a significant role in driving systemic risk, especially during crises, underscoring the need for transparent and stable policymaking. Additionally, while macroeconomic shocks have a delayed influence on systemic risk, their impact on EPU is relatively limited. The findings stress the importance of adaptive policy responses that can address both immediate and lagged risks, ensuring financial stability in the face of evolving economic challenges.

**iii. Keywords**

Economic Policy Uncertainty (EPU), Systemic Risk (SYS), Macroeconomic Shocks (MS), Cross-Quantilogram (CQ) Analysis, Financial Stability, Lagged Dependencies, Proactive Policymaking, Quantile Analysis

**1. Introduction**

The dynamics between economic policy uncertainty (EPU), macroeconomic shocks (MS), and systemic risk (SYS) are crucial for understanding financial stability, particularly in emerging economies such as India. As uncertainties in economic policies and external macroeconomic shocks increasingly contribute to systemic vulnerabilities in financial markets, it becomes essential to examine how these factors interact and influence overall financial health.

This study utilizes monthly data from January 2000 to June 2024 to investigate the relationships among these variables through advanced statistical methods, particularly Cross-Quantilogram (CQ) analysis. This technique allows for an examination of the dependencies between the variables across different quantiles, focusing on both extreme events, such as financial crises, and more moderate occurrences. By analyzing these dynamics, the research aims to identify key periods when the relationships between EPU, MS, and SYS intensify, providing policymakers with insights that could inform targeted intervention strategies.

The findings indicate that while EPU has an immediate impact on systemic risk, macroeconomic shocks tend to affect SYS with a delay, which provides a critical window for policymakers to enact mitigation strategies. The study further underscores the importance of stable, transparent, and proactive policymaking to address the vulnerabilities posed by both immediate and delayed economic shocks. By exploring quantile-specific and lag-specific dependencies, this research offers valuable insights into systemic risk management, emphasizing the need for adaptive and responsive policy frameworks in the face of evolving economic conditions.

**2. Literature Review**

**2.1 Economic Policy Uncertainty (EPU)**

Research on Economic Policy Uncertainty (EPU) has grown significantly, emphasizing its impact on financial markets and macroeconomic activity. Bordo et al. (2016) demonstrate that heightened EPU restricts U.S. credit growth, particularly during financial crises, amplifying economic downturns. Similarly, Caldara et al. (2020) and Al-Thaqeb et al. (2021) highlight EPU’s global ripple effects, showing declines in stock markets, GDP, and output due to delayed investments and cautious consumer spending. Chen & Zhao (2021) reveal asymmetric effects of EPU on Chinese stock returns, with stronger negative impacts during downturns and positive impacts in favorable conditions.

In developing economies, Feng et al. (2023) show EPU-driven risk spillovers across Belt and Road Initiative (BRI) countries, while Yu and Gong (2019) find that rising EPU in China curtails bank credit growth, increasing financial instability. Fang et al. (2023) decompose systemic risk, finding EPU raises systemic linkages despite reducing bank tail risks. Studies like Phan et al. (2021) confirm EPU's adverse effects on global financial stability, with impacts amplified by high competition and weak regulatory frameworks. Advanced methods such as VAR, DCC-GARCH, and quantile-based approaches further underscore EPU’s critical role in shaping financial and macroeconomic dynamics.

### **2.2 Systemic Financial Risks (SYS)**

Research on systemic financial risk highlights its critical role in financial stability, particularly during crises. Brownlees and Engle (2017) introduce the SRISK model, demonstrating that capital shortfalls in interconnected institutions amplify systemic risk during financial stress. Similarly, Diebold and Yilmaz (2014) analyze connectedness in financial firms, finding that high interconnectivity increases contagion risks, especially during periods of policy uncertainty.

Coudert and Gex (2013) explore the link between Credit Default Swaps (CDS) and bond markets, showing that heightened EPU exacerbates systemic risks through increased volatility. This aligns with Freixas et al. (2015), who emphasize the role of macroprudential regulation in mitigating systemic risk, while cautioning against uncertainty in policy implementation.

Global market interactions are further explored by Fasanya et al. (2021), who find that EPU amplifies systemic risks in oil and forex markets, causing broader financial instability. In Europe, Karimalis & Nomikos (2018) identify liquidity risk, leverage, and bank size as significant contributors to systemic risk using a Copula CoVaR approach, while Stolbov & Shchepeleva (2020) highlight systemic risk’s role in driving firm bankruptcies across multiple regions. Enhanced measurement frameworks, like the modified CoVaR by Girardi et al. (2013), provide more consistent tools for assessing systemic risk under dynamic conditions.

### **2.3 Macroeconomic Shocks**

Macroeconomic shocks, such as financial crises, trade conflicts, and global pandemics, significantly affect economic growth, financial markets, and policy effectiveness. Bloom (2009) identifies macroeconomic shocks as a key driver of volatility, with their unpredictability leading to widespread uncertainty in investment and output. Born and Pfeifer (2014) emphasize that frequent shocks force economic entities to adopt precautionary saving, dampening investment and slowing macroeconomic recovery.

During global crises, shocks from advanced economies have profound spillover effects. Chuliá et al. (2017) find that U.S. macroeconomic shocks, particularly during crises, cause significant output declines and capital flow volatility in emerging markets. Similarly, Creal and Wu (2014) highlight how monetary shocks in the U.S. heighten output and inflation volatility, revealing the interconnected nature of global markets.

The financial sector often acts as a conduit for macroeconomic shocks. Bordo et al. (2016) show that shocks during financial crises restrict credit channels, amplifying economic downturns. Fang et al. (2023) find that macroeconomic instability is exacerbated by systemic financial risks, as shocks increase interlinkages among institutions, magnifying potential disruptions.

Cross-border implications of shocks include capital outflows and weakened monetary policy transmission, especially in developing economies (Das et al., 2019; Kim and Yang, 2012). These studies underscore the importance of robust financial systems and proactive macroeconomic policies to cushion the impact of shocks and promote long-term economic stability.

### **2.3 Cross-Quantilogram (CQ)**

The Cross-Quantilogram (CQ) method is a powerful tool for analyzing asymmetric and nonlinear relationships across different quantiles, making it particularly valuable for studying financial dynamics under varying market conditions. Feiyun Xiang and Yimang Fu (2024) utilize CQ to examine how Trade Policy Uncertainty (TPU) affects insurance premiums in China. Their findings reveal that TPU has a short-term negative impact on premiums, likely due to immediate market disruptions, but fosters demand for risk protection over the long term, leading to positive effects. Similarly, Yu Wang et al. (2024) employ CQ to explore the influence of Economic Policy Uncertainty (EPU) and Climate Policy Uncertainty (CPU) on China’s Green Finance market, finding that these uncertainties significantly affect green bonds and stocks differently across quantiles, highlighting the method's ability to capture complex causal relationships.

In a broader systemic risk context, the CQ network approach, as demonstrated by Eduard Baumöhl et al., provides insights into systemic vulnerabilities within global banking networks. The method identifies critical nodes and their interdependencies under varying risk conditions, emphasizing its utility for policy interventions in the face of economic shocks.

**3. Data**

**3.1. Sample**

A total of 6 listed companies in India which include banks and are a part of the securities sector were selected as the sample of financial institutions of India. This sample represents the financial industry as a whole. The market value of these companies is very significant and it is enough to reflect all the financial institutions. The data used in this paper is from January 2000 to June 2024 based on its availability, and NSE Bank Nifty index is used as the financial market monthly yield measurement index. We also weighted each of the financial institutions based on their current market values. We have extracted the data used in this paper from the Bloomberg Terminal.

**3.2 Economic Policy Uncertainty**

In this paper, we construct the Economic Policy Uncertainty on news based indices. First, we do keyword searches from newspapers such as Times of India, Economic Times, and The Hindu.

Monthly data is accumulated and aggregated to create a time series index of economic policy uncertainty. Then we convert this monthly data to annual averages to find broader trends.

India’s EPU index shows many notable and important fluctuations based on several different domestic and international events. The early 2000’s had several fluctuations because of events that took place at the time, certain scams and some global events. The global crisis of 2008 marks a peak because of the housing crisis that took place. Demonetisation in 2016 caused a sharp spike in uncertainty, especially the cash related sectors. Similarly, demonetisation causes a lot more uncertainty. Even the Covid 19 pandemic caused a lot of uncertainty, all of which led to a new normal in the economy. Even the Russia - Ukraine crisis caused uncertainty in the economy. Even some domestic specific events took place such as the IL&FS crisis in 2018 and Adani stock volatility in 2023 went from uncertainty to broader economic stability over time.

**3.3 Systemic Financial Risk**

𝛥𝐶𝑜𝑉𝑎𝑅was used to study systemic financial risk in our paper. We use the rate of return to measure the systemic risk, which takes into account the tail risk. Similar to the earlier case, we use the market capitalization and value method to help us calculate the systemic risk of financial sectors. This is done so that the extremes or ends of smaller weight do not affect the whole as much thus making it less susceptible to some financial institutions going really high or low. We focus on our specific industry and not the market as a whole, which is why we calculate the specific industry systemic risk. Also, if we take the market as a whole, a significant difference in one institution in the industry does not affect the market, which makes it less accurate for our calculations. This is why we do not use the industry index to measure systemic risk.

𝛥𝐶𝑜𝑉𝑎𝑅is the risk the other financial institutions face when one financial institution faces. Now, the tail risk or the extremes is what is important at the time, so we have a normalized model which is -

Generalised CoVaR considers crisis events and helps in reflecting tail risks. More importantly, it tells us about how the financial market responds during emergencies, which is why we tend to use this model. Existing research on CoVaR estimations has included quantile regression, DCC-GARCH, and Copula. We use the DCC-GARCH model so that we can better measure the time-varying process, the DCC-GARCH model was used to estimate the CoVaR. This is done after assuming that institutions follow the bivariate normal distribution model, and we come to this idea.

𝜌 - dynamic conditional correlation coefficient

𝑠𝑖𝑔𝑚𝑎 - conditional standard deviation

When the markets are in a state of loss, they follow a normal distribution, this is how the normal distribution works. Based on it,

Based on the COVAR definition,

As,

the CoVaR calculation formula is:

Based on this, we calculate A using:

In the end, financial market systemic risk was obtained using the weighted market value of the financial institutions:

where is the market value of firm in year .

Macroeconomic indicators include GDP, CPI, deflation, investment indicators, consumption, macroeconomic prosperity index, purchasing manager index, industrial added value growth rate, etc. For some indicators such as purchasing manager index, we found the exact value from 2010 to 2024, but for some indices, we decided to find a proxy for them based on which are suitable for the Indian market. The idea of using macroeconomic variables is that when we look at the fluctuation of these specific variables, it gives us a very good idea of the actual trend of macroeconomics. They gave us a pretty good idea of how it worked and how the trend moved as a whole. Lets take an example, PMI is a composite indicator that measures the monthly change in the output of the manufacturing and service sectors, so it told us about how business related activities in that sector moved, giving us an idea of the overall demand and supply at the time.

In India, the PMI is not conducted by the government, instead, it is conducted by private agencies or independent institutions which help in providing monthly data for the manufacturing and service sectors. The survey collects data from business executives from private sector companies who provide the appropriate data.

The sample size of industries is divided in a way such that those with more value in the market have a higher value addition to the total industry.

The data is collected by this independent institution and then given to us in the form of PMI.

This paper selected the PMI and a few other proxies for macroeconomic trends from the perspectives of production, investment, consumption, import and export.

We took the data as per availability from Jan 2000 to June 2024, reducing the time span in certain cases based on the availability of data.

In cases of imports and exports, we took data of the price of certain important commodities which have a market beta close enough to the real macroeconomic trends. We collected all of this data from the Bloomberg Terminal.

The next thing we did was standardizing the macroeconomic data, because all of these had different values and we had to make them relative. So we unified the dimensions. Then, we calculate the correlation coefficient matrix, the eigenvalues, and the corresponding eigenvectors. The eigenvalues are lined up from largest to smallest: Then we calculate the value provided by each of these variables to the whole by calculating their weight to the overall weight. Each of these were called principal components. Then, we expressed each in the form of a linear regression, and calculated their respective factor scores. After weighing it, we summarized it to obtain a new time series equation, which was :

Also, we define residual shocks as a macroeconomic shock, we got its formula as,

- constant,

- parameter,

- random perturbation term.

**4. Methodology**

**Cross-Quantilogram (CQ) Method**

This study utilizes the Cross-Quantilogram (CQ) methodology, which is designed to examine the dependence and directional predictability between time series across different quantiles. It is particularly effective in capturing the dynamics of extreme events, focusing on the tail relationships among three stationary series: . Developed by Han et al. (2016), the CQ method analyzes the cross-correlation between two stationary time series, with a key advantage being its ability to identify the direction of the relationship. This means it can determine which variable predicts the past values of the other through lagged observations. Additionally, the CQ method calculates this directional predictability across various quantile levels of the return distribution. Han et al.'s (2016) approach stands out from other network-based methods, such as those proposed by Belloni et al. (2016), Zhu et al. (2019), and Chen et al. (2019).

The CQ methodology distinguishes itself from other network-based quantile approaches, such as those put forward by Belloni et al. (2016), Zhu et al. (2019), and Chen et al. (2019). For example, Belloni et al. (2016) introduced two types of quantile graphical models: conditional independence quantile graphical models (CIQGMs), which assess the conditional independence of distributions at various quantiles, and prediction quantile graphical models (PQGMs), which uncover dependencies using superior linear predictors. In contrast, Zhu et al. (2019) concentrate on network quantile autoregression (NQAR) models, where the adjacency matrix is considered an exogenous variable, and its estimation is not integrated into the model itself. Meanwhile, Chen et al. (2019) proposed the tail-event driven network quantile regression (TENQR) model, which accounts for systemic risk by emphasizing significant downside risks and uses an empirically derived adjacency matrix based on conditional expected shortfalls.

**4.1 Quantile-Based Dependence**

The CQ method focuses on analyzing the conditional quantile of each series. For a given time series at time t, the behavior at specific quantiles is examined using the **conditional quantile function**. This function is defined as: , where represents optional conditioning variables, and indicates the quantile level (e.g., for the quantile).  
To measure the deviations from quantile thresholds, the quantile hit process is defined as:

, where is an indicator function returning 1 if , and 0 otherwise.

**4.2 Cross-Quantilogram for Pairwise Dependence**

The Cross-Quantilogram (CQ) for pairwise dependence quantifies the directional dependence between two time series,, at different quantiles and lags. It compares the deviations of each series from its respective quantile to measure the correlation at a specific lag k. The formula captures the strength and direction of the relationship, with values constrained between 0 and 1, indicating the intensity of dependence between the series across quantile levels. For each pair of series , the lagged directional dependence is computed using the cross-quantilogram:

**4.3 Joint Quantile Dependence for Three Series**

The joint quantile hit process assesses the simultaneous dependence between three series by evaluating whether each series exceeds its respective quantile threshold. It uses an indicator function to capture the joint occurrence of exceedances across at specific quantiles, providing a measure of their collective dependence.

The Joint Cross-Quantilogram (JCQ) extends the CQ method to analyze the dependence between multiple time series simultaneously. It computes the directional dependencies among three time series, at various quantiles and lags. The JCQ captures the joint interaction between the series by considering the combined deviations from their respective quantile functions

**4.4 Hypothesis Testing for Directional Predictability**

To assess directional predictability in the quantiles of return distributions, Han et al. (2016) propose a Ljung-Box type statistic. This test compares the null hypothesis of no directional predictability against the alternative of its presence up to a specified number of lags.

**Null Hypothesis:** where is the number of lags.

The test statistic is computed as: where is the sample size.

**4.5 Systemic Risk Measurement and Network Construction**

A directed network with nodes representing the three series and edges denoting significant quantile dependencies. The adjacency matrix is defined as: is statistically significant, and 0 otherwise. Systemic Risk Score is calculated as where is a vector of weights reflecting the relative importance of each series. This score quantifies the systemic risk based on the interdependencies within the network.

**5. Empirical results and discussion**

**5.1 Augmented Dicky Fuller (ADF) Test**

This paper used the ADF test to test the stability of each variable. The test results are shown in the Table below.

| Column | T-Value | P-value | Stationarity |
| --- | --- | --- | --- |
| EPU | -6.839973722 | 0.0000000018016495 | Stationary |
| SYS | -7.429795748 | 0.0000000000640537 | Stationary |
| MS | -10.83749207 | 0.0000000000000000 | Stationary |

The table shows that all three variables, EPU, SYS, and MS, are stationary based on their ADF test statistic (T-values) and extremely low p-values. The variables of all the three variables being lesser than the critical 1% significance level rejects the null hypothesis of a unit root existence which proves that they are stationary.

**5.2 Granger-Causality Test**

To test the statistical causality among the variables, Granger-Causality was performed on Economic Policy Uncertainty Index (EPU), Macroeconomic Shock Index (MS), Systemic Risk Index (SYS), the results are shown below in the table.

| Independent Variable | EPU | | SYS | | MS |  |
| --- | --- | --- | --- | --- | --- | --- |
| T-Statistic | P-Value | T-Statistic | P-Value | T-Statistic | P-Value |
| EPU | - | - | 2.323 | 0.022\*\* | 0.587 | 0.559 |
| MS | 1.862 | 0.065\* | 0.177 | 0.86 | - | - |
| SYS | 1.67 | 0.098\* | - | - | 1.087 | 0.279 |

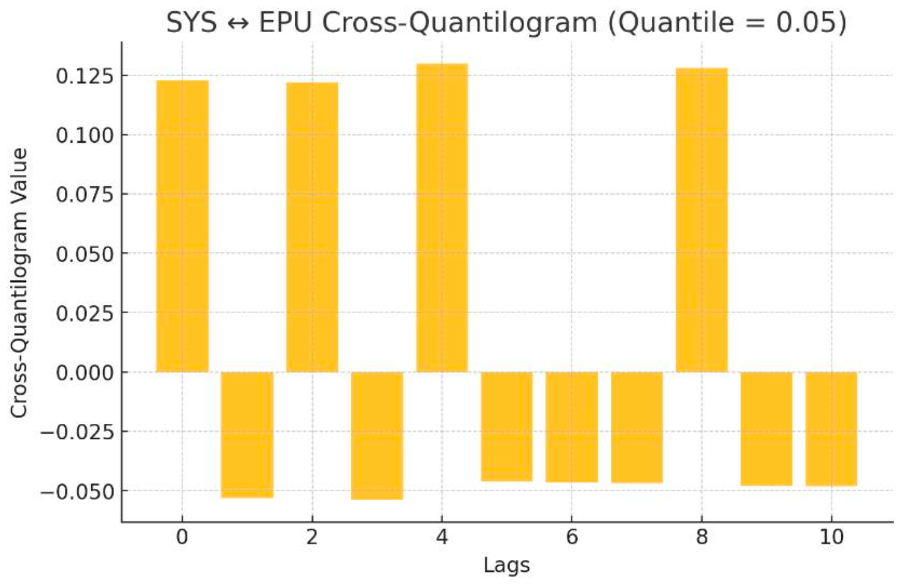
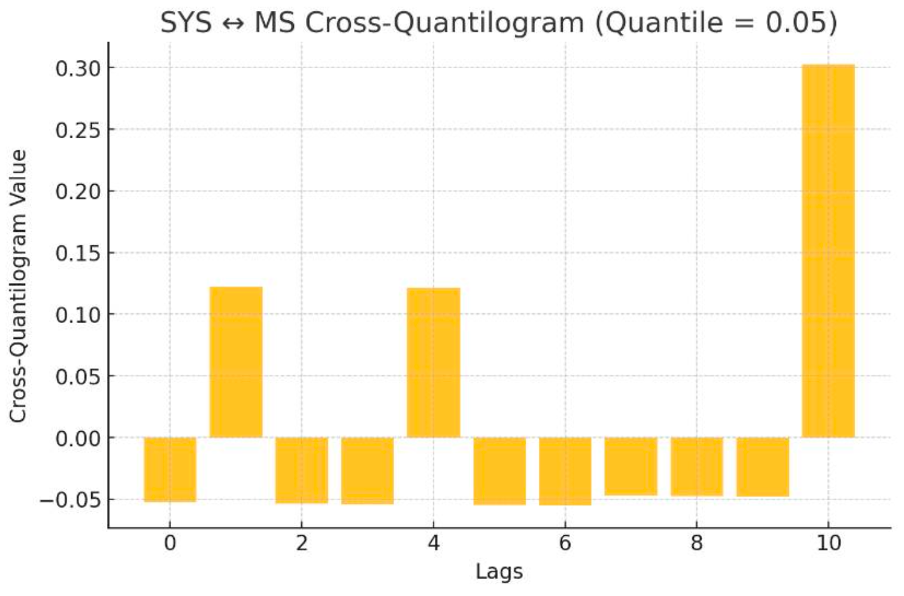
Note: asterisks indicate statistical significance at the 95% (\*\*) or 90% (\*) levels, respectively.

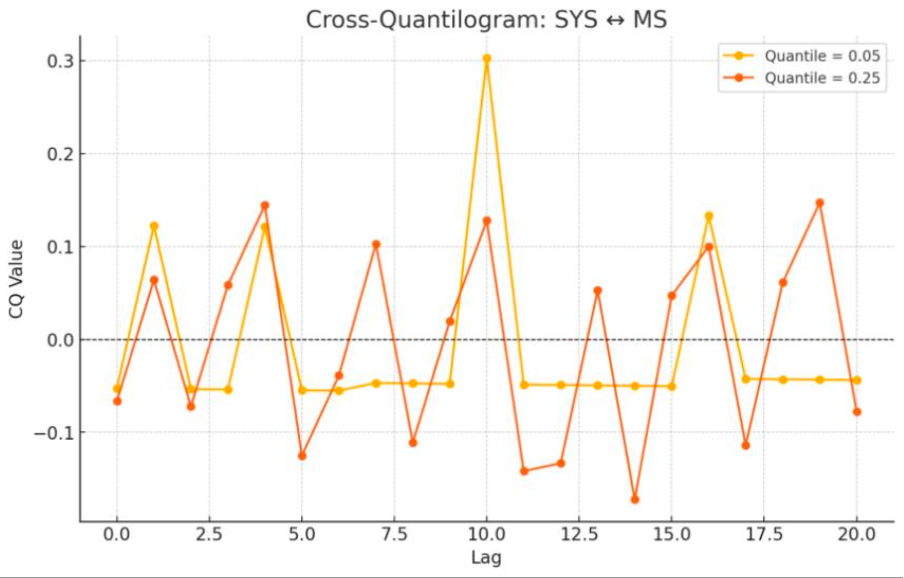
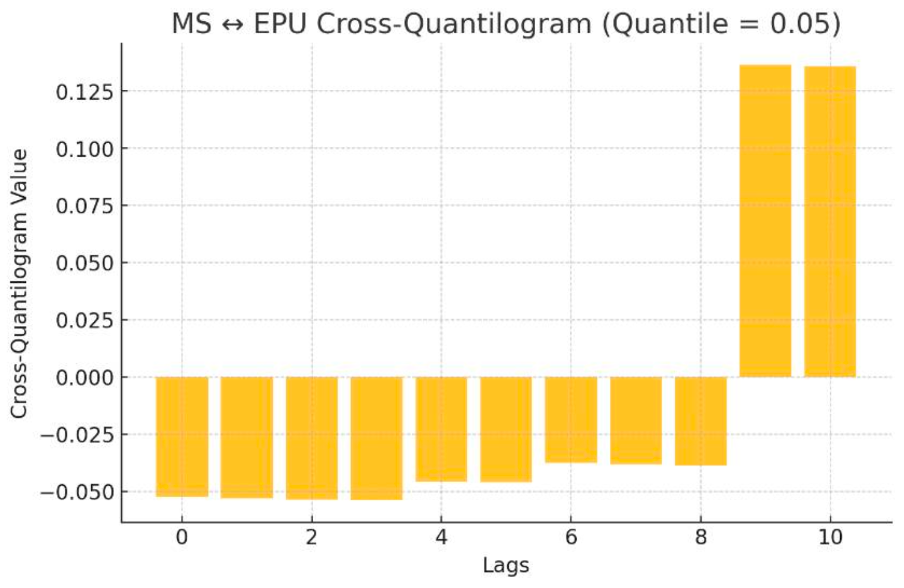
The Nonlinear Granger Causality test results table shows that economic public uncertainty (EPU) has strong causality with Systemic Risk (SYS), i.e. EPU → SYS, Macroeconomic shock (MS) and Systemic risk (SYS) have little causality with EPU, i.e. MS → EPU and SYS → EPU respectively, while there is no significant causality for the remaining combinations EPU → MS, MS → SYS, and SYS → MS.

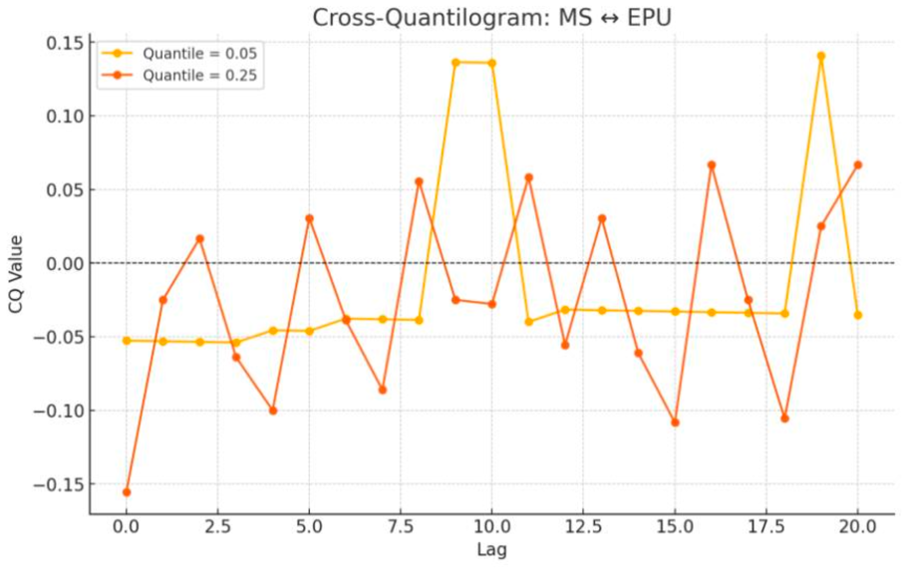
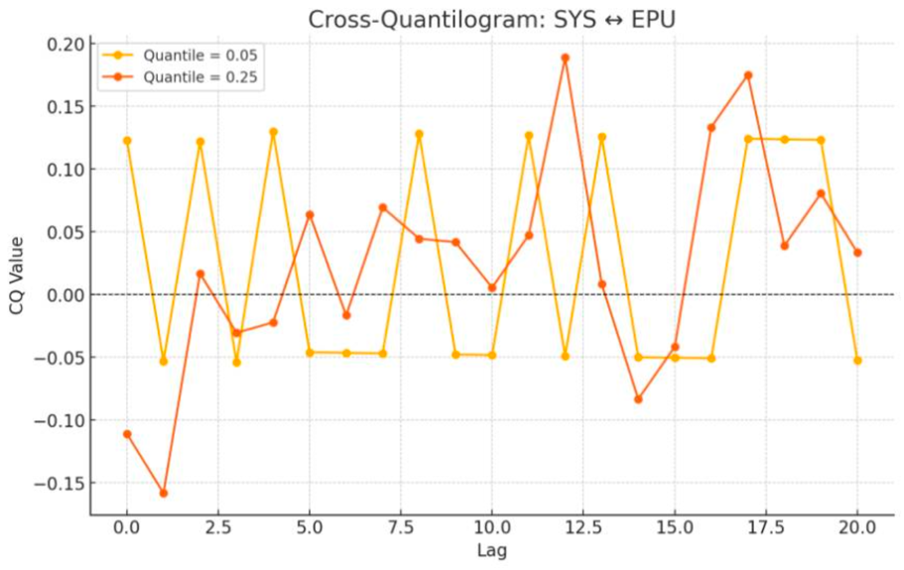
### **5.3 Cross-Quantilogram (CQ) Analysis**

#### The cross-quantilogram analysis computes CQ values. This measure the directional dependencies between variables at specific quantiles and lags. We analyzed the 0.05 (for extreme events) and 0.25 (for moderate events) quantiles at lags up to 20, to represent delayed impacts.

The line plots and bar plots show CQ values across lags for variable pairs. SYS-MS shows delayed dependencies with the strongest effects at lag 10. This tells us that MS has a delayed impact on SYS. SYS-EPU shows immediate effects at lag 0, stabilizing over longer lags. This tells us that EPU has an immediate impact. MS-EPU shows weak dependencies overall, and peaks at lag 9. This tells us that EPU does not affect MS over time.



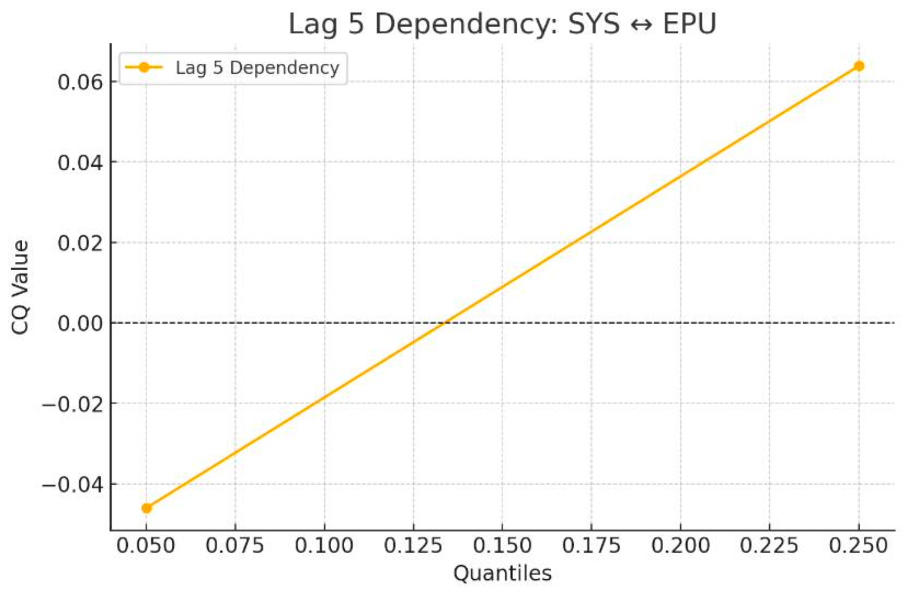
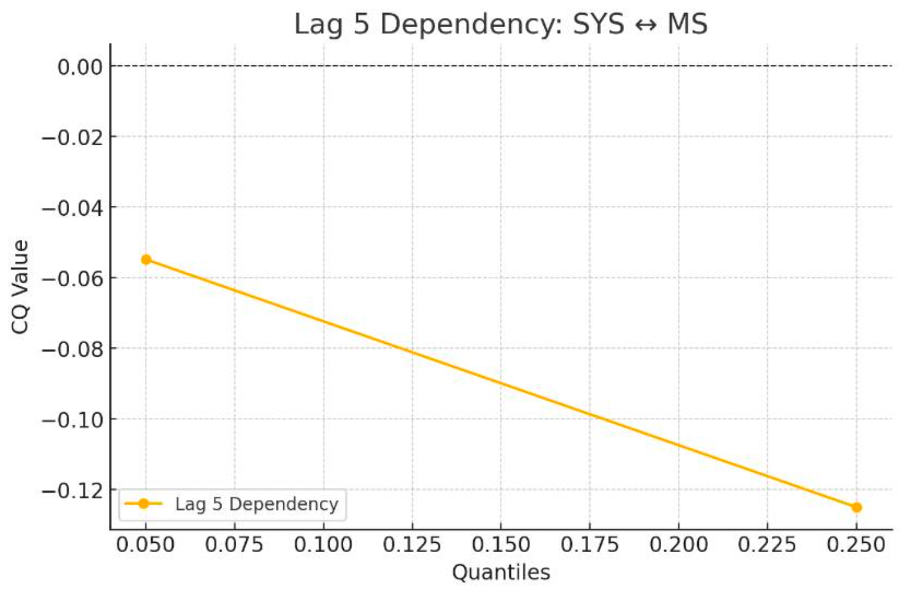


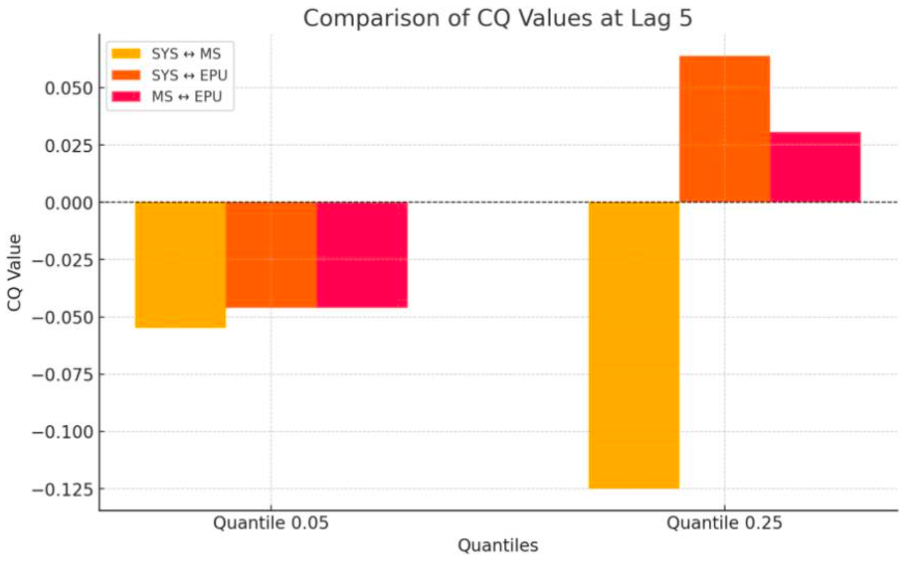
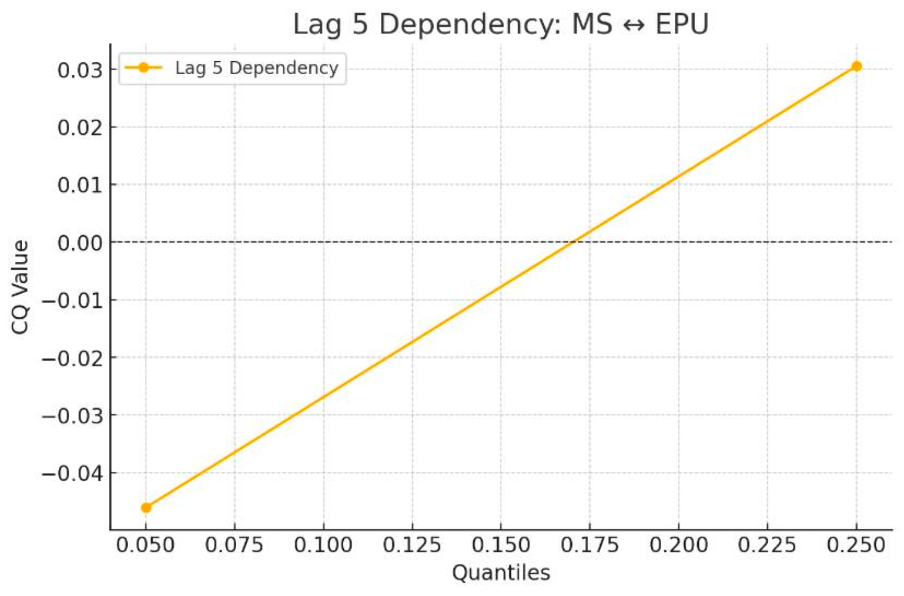


### **5.3.1 Studying CQ variation across quantiles for specific lags**

**Lag 5:**

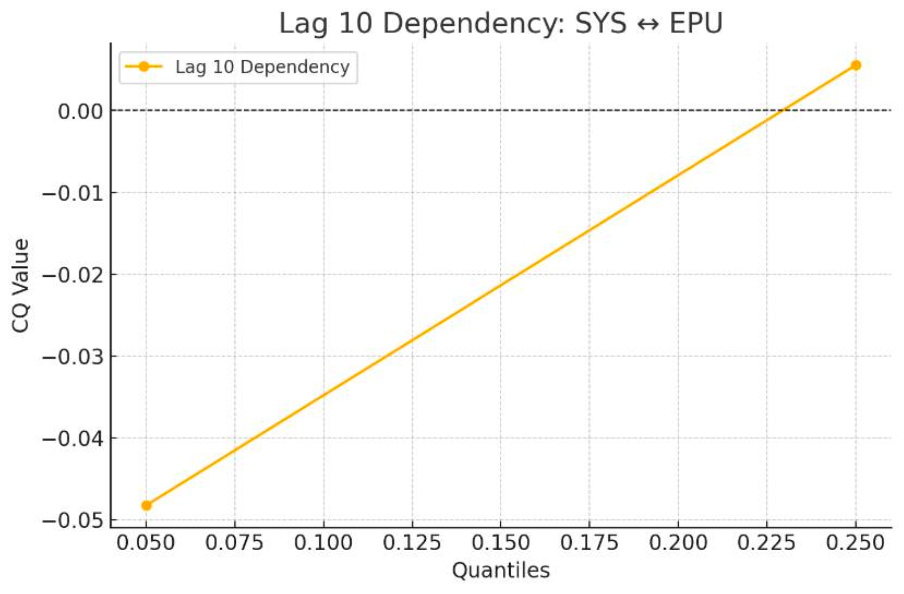
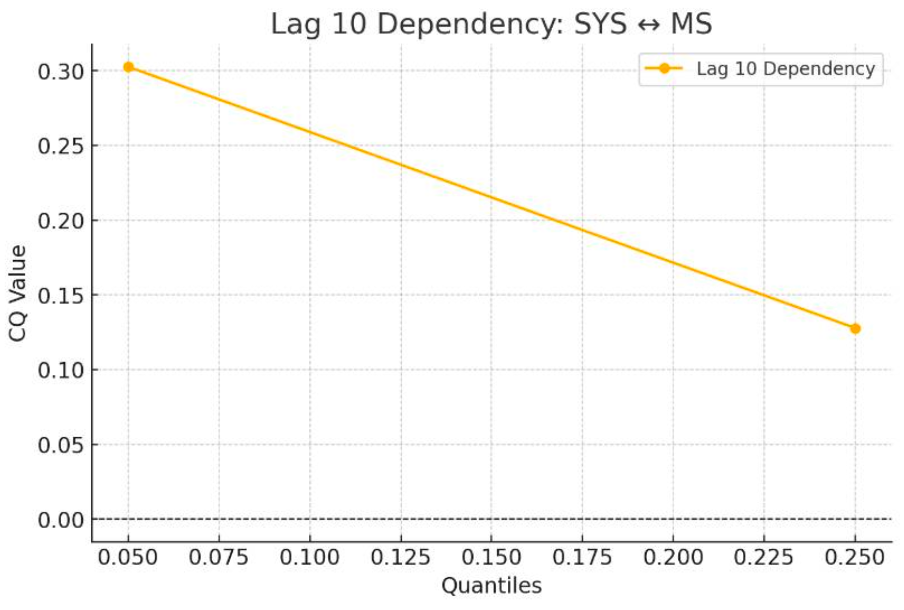
1. **SYS ↔ EPU**: The dependency is negative at extreme quantiles (0.05), indicating weaker immediate links between systemic risk and policy uncertainty during crises. At higher quantiles, the dependency strengthens, showing that policy uncertainty plays a stabilizing role over a short delay in less extreme conditions.
2. **SYS ↔ MS**: The dependency is consistently negative, suggesting that macroeconomic shocks tend to dampen systemic risk over a short lag. The effect is stronger at higher quantiles, reflecting stabilizing macroeconomic dynamics in moderate conditions.

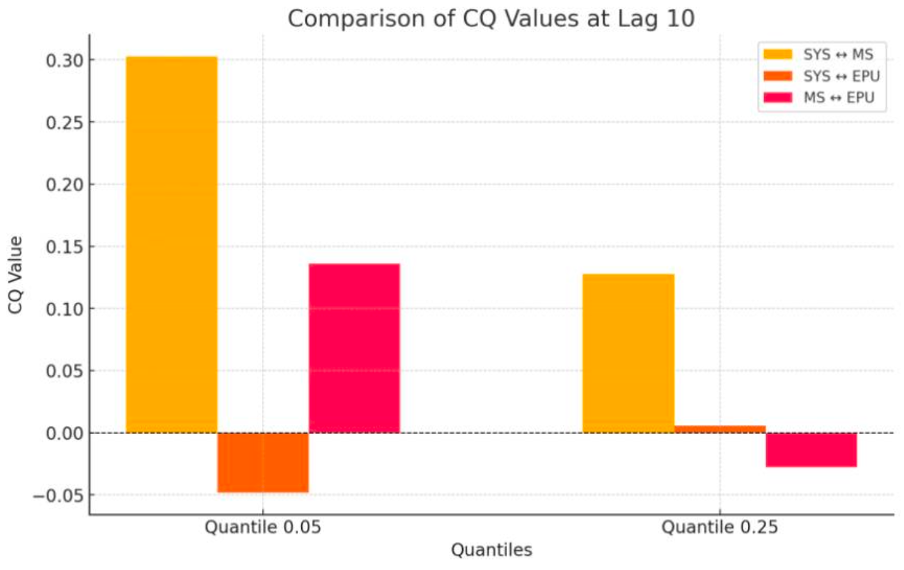
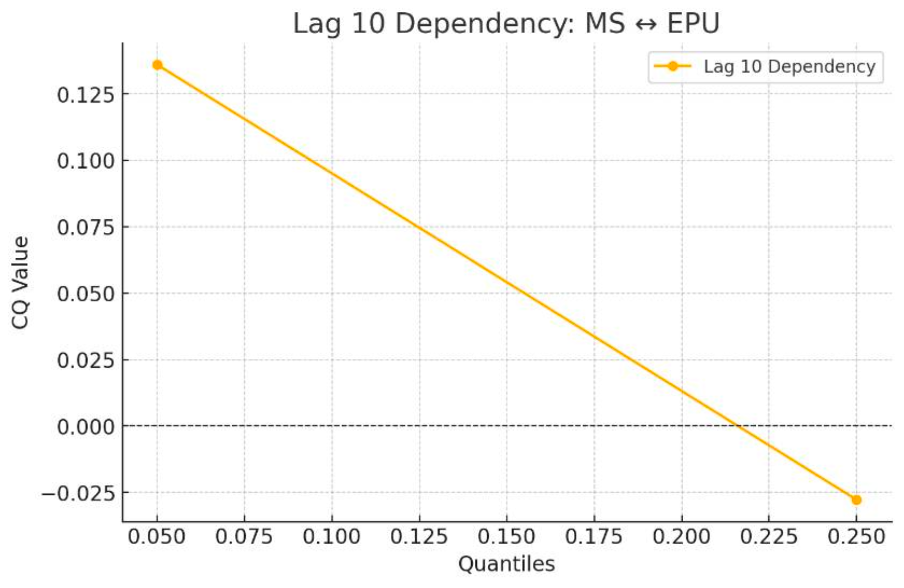




### **Lag 10:**

1. **MS ↔ EPU**: Strong dependencies at extreme quantiles (0.05) suggest delayed macroeconomic impacts on policy uncertainty during crises. The dependency weakens at higher quantiles, indicating reduced alignment in moderate conditions.
2. **SYS ↔ EPU**: Negative dependencies at extreme quantiles highlight an initial decoupling of systemic risk from policy uncertainty. Positive values at higher quantiles show that over time, policy uncertainty supports systemic risk stabilization.
3. **SYS ↔ MS**: Strong dependencies at extreme quantiles reflect the delayed propagation of macroeconomic shocks on systemic risk during crises. Declining values at higher quantiles suggest that the relationship weakens in less volatile conditions.



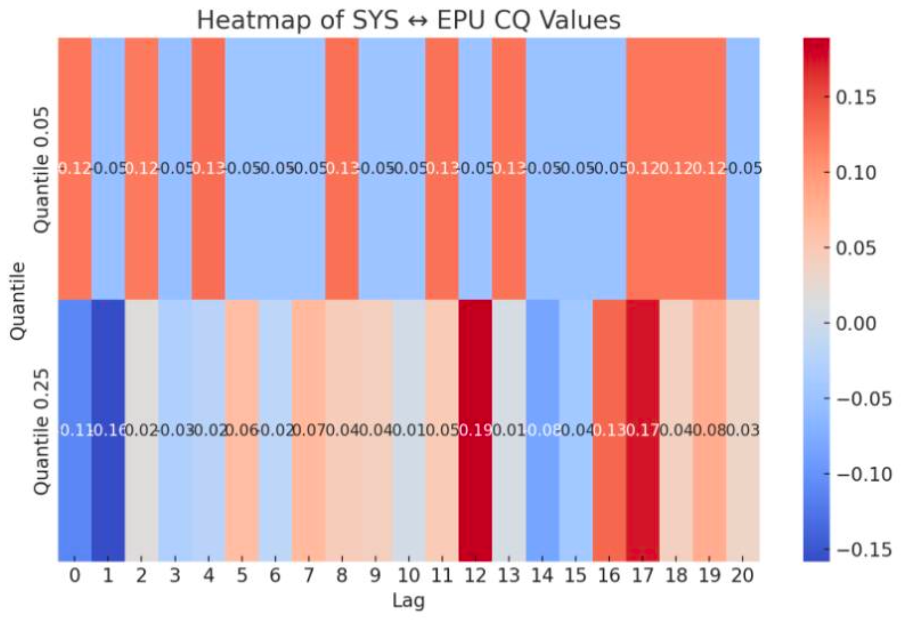
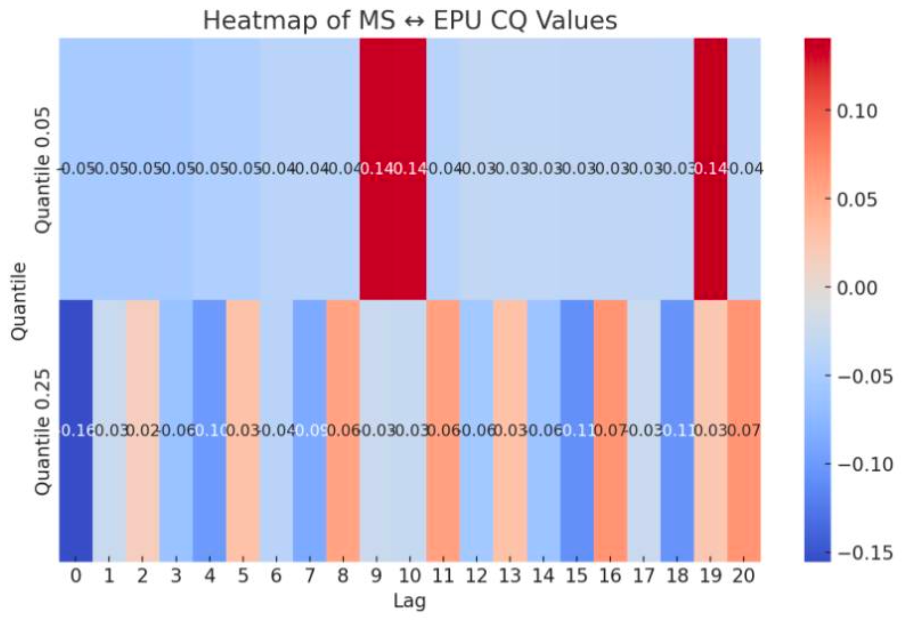


**Summary of CQ Analysis:**

|  | Variable Pair | Quantile | Lag | CQ Value | 95% CI Lower | 95% CI Upper |
| --- | --- | --- | --- | --- | --- | --- |
|  | SYS MS | 0.05 | 10 | 0.303 | -0.041 | 0.334 |
|  | SYS MS | 0.25 | 4 | 0.144 | -0.043 | 0.177 |
|  | SYS EPU | 0.05 | 0 | 0.123 | 0.122 | 0.126 |
|  | SYS EPU | 0.25 | 17 | 0.175 | -0.052 | 0.210 |
|  | MS EPU | 0.05 | 9 | 0.136 | -0.053 | 0.152 |
|  | MS EPU | 0.25 | 17 | 0.066 | -0.056 | 0.090 |

The table summarizes the Corrected Quantile (CQ) analysis for various variable pairs at different quantiles and lags. For the pair SYS ↔ MS, the highest CQ value (0.303) is observed at the 0.05 quantile with a lag of 10, indicating a strong relationship in the lower quantile region. Similarly, for SYS ↔ EPU, the CQ value at the 0.25 quantile and lag 17 is relatively higher (0.175) with a 95% confidence interval range of -0.052 to 0.210, showing a moderate dependency. The pair MS ↔ EPU shows the weakest relationship, particularly at the 0.25 quantile and lag 17, with a CQ value of 0.066 and a narrow confidence interval range (-0.056 to 0.090), suggesting minimal dependence. Overall, stronger associations are observed in lower quantiles across different lags.

The heat maps depicting quantile-lag dependencies highlight the strength and asymmetry of dependencies across quantiles. SYS-EPU shows magnified effects in extreme quantiles, while SYS-MS emphasizes delayed impacts.





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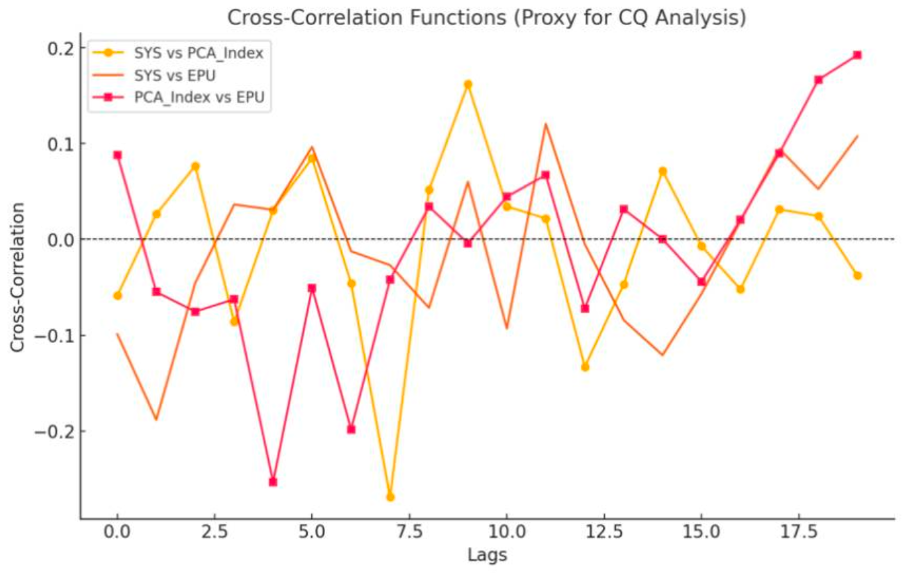
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### **5.4 Joint Quantile Analysis**

Joint quantile analysis computes the joint frequency of extreme quantile hits (quantile < 0.05) for SYS, MS, and EPU.The time series plot highlights periods with simultaneous extreme quantile hits across all three variables.



The plots above provide a preliminary look at the relationships between the variables through cross-correlation functions, serving as a simpler proxy for the Cross-Quantilogram (CQ) analysis. Specifically, they show how systemic risk (SYS) interacts with macroeconomic shocks (PCA\_Index) and economic policy uncertainty (EPU) over varying time lags. Additionally, the correlation between macroeconomic shocks (PCA\_Index) and policy uncertainty (EPU) is also explored, offering insights into their interconnected behavior across time.

**5.5 Robustness Test**

Robustness tests are crucial in econometrics for several reasons, helping ensure the credibility, reliability, and validity of empirical findings. Robustness tests check whether the main results hold true under different conditions or assumptions. In econometrics, different choices of variables, functional forms, or econometric models can influence the outcome. If the results remain consistent across various specifications, it increases confidence in the validity of the conclusions.Econometric models often rely on a set of assumptions (e.g., no endogeneity, no omitted variable bias, homoscedasticity). Robustness checks help test the sensitivity of the results to these assumptions. If the results change significantly when assumptions are relaxed or modified, it suggests that the findings might be sensitive to these assumptions, calling for caution in interpretation.

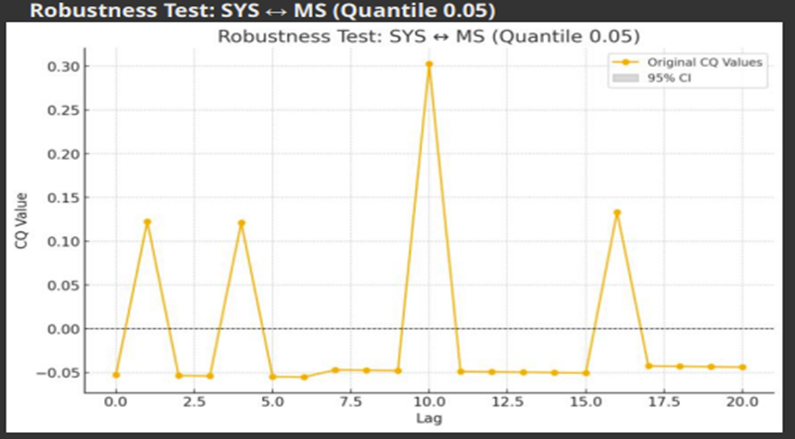
**5.5.1** **Stationary Bootstrap Method**

1. **SYS ↔ MS (Systemic Risk ↔ Macroeconomic Shocks)**

The original CQ values indicate moderate positive dependencies at certain lags.

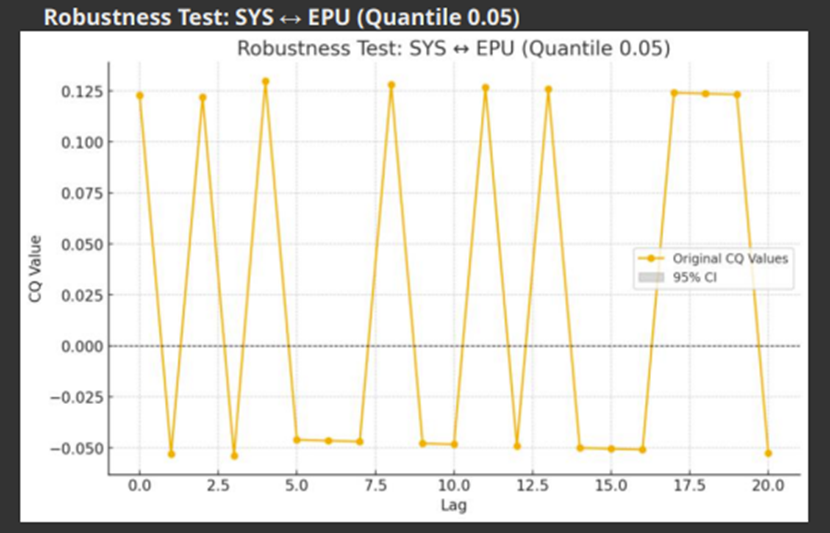
The 95% bootstrap confidence intervals validate the statistical significance of the dependencies

at key lags. Dependencies are most significant around lag 10.



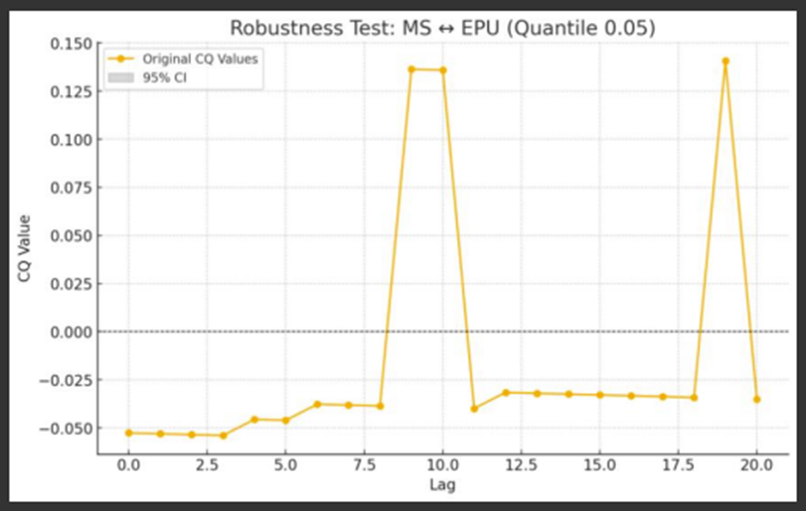
1. **SYS ↔ EPU (Systemic Risk ↔ Economic Policy Uncertainty)**

The CQ values highlight stronger dependencies, particularly at shorter lags (0–5). Condence intervals show that these dependencies are statistically robust, reinforcing the role of EPU in influencing systemic risk.



1. **MS ↔ EPU (Macroeconomic Shocks ↔ Economic Policy Uncertainty)**

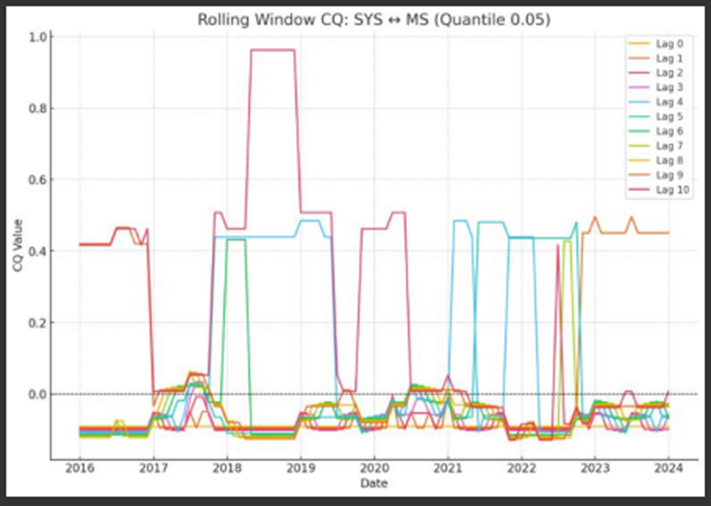
Dependencies are weaker overall but show notable positive values at lag 9. Confidence intervals confirm that the observed relationships at specific lags are statistically significant.

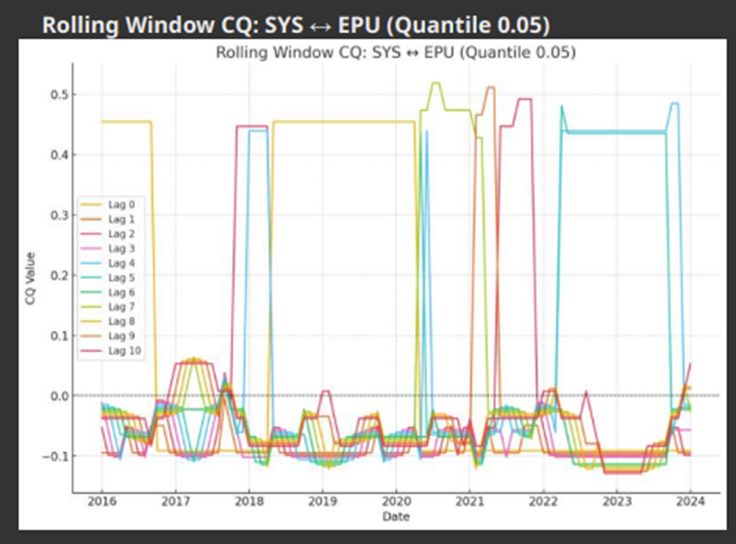


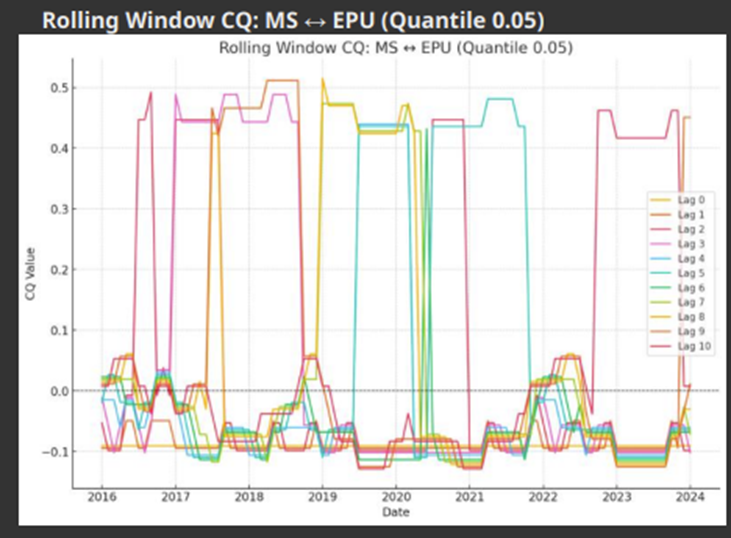
The connection between SYS and EPU stands out as the strongest and most immediate, showing a clear and direct link. On the other hand, the relationship between SYS and MS takes longer to emerge and is most noticeable during extreme conditions, pointing to a more complex, situational dependency. To make sure these patterns weren’t just random, bootstrap confidence intervals were used, confirming that the observed relationships are meaningful and reliable.

**5.5.2 Rolling Window Robustness Test**

A rolling window robustness analysis is a method used in econometrics and time series analysis to assess the stability and robustness of estimated coefficients, model performance, or relationships over time. It involves estimating a model over a moving (or rolling) subset of the data, typically using a fixed-size window that shifts sequentially through the dataset.







**6. Conclusion and Policy Implications**

This study provides a comprehensive analysis of the dynamic interaction between systemic risk (SYS), macroeconomic shocks (MS), and economic policy uncertainty (EPU) in the Indian economy using the Cross-Quantilogram (CQ) methodology. The results show that EPU has an immediate impact on SYS, particularly during crises, highlighting the critical role of transparent and consistent policymaking to mitigate systemic risks. MS, on the other hand, influences SYS with a time lag, indicating that policymakers have a window of opportunity to implement risk mitigation strategies post-shock.

Our results further reveal that the dependencies between SYS and EPU are stronger and more persistent compared to those between MS and EPU, suggesting that policy uncertainty is a more critical driver of systemic risk than macroeconomic shocks in the short term. Joint quantile analysis highlights periods of overlapping risks, where simultaneous extremes in SYS, MS, and EPU demand coordinated and multidimensional policy interventions.

In the post-COVID era, while the resilience of the economy to macroeconomic shocks has improved, the continued strong dependency of SYS on EPU underscores the need for policy stability and predictability. The rolling window and robustness tests confirm the validity of these relationships across varying economic conditions, solidifying the importance of adaptive and proactive policy frameworks in ensuring financial stability and mitigating systemic risks effectively.

Systemic risk (SYS) exhibits immediate sensitivity to changes in economic policy uncertainty (EPU), highlighting the critical need for stable policies during crises. Instability in policymaking during such periods can lead to volatile reactions, exacerbating systemic risk. Additionally, the delayed effects of macroeconomic shocks (MS) on systemic risk provide policymakers with a valuable timeframe to implement strategies aimed at mitigating potential risks. These time-lagged impacts of MS emphasize the importance of proactive measures in the aftermath of economic disruptions.

The dynamic interplay between SYS, MS, and EPU becomes especially pronounced during financial crises, where heightened correlations signal critical periods that demand targeted policy interventions. EPU’s persistent influence, even during relatively stable economic conditions, underscores the importance of consistent and transparent policy frameworks as a cornerstone of effective risk management. The cumulative effects observed across time indicate that while policy-related shocks require swift responses, macroeconomic shocks allow for more measured interventions, granting policymakers the opportunity to navigate risks strategically.

In the post-COVID era, the relationship between SYS and MS has weakened, suggesting that global economies have developed greater resilience to macroeconomic shocks. However, the consistent dependency of SYS on EPU demonstrates that policy uncertainty remains a significant driver of systemic risk. Joint analyses of these variables reveal high-risk periods where their convergence necessitates coordinated, multidimensional responses. Policymakers must adopt comprehensive strategies to tackle these overlapping challenges and ensure economic stability during critical moments.

Overall, EPU remains a persistent factor driving systemic risk, reinforcing the need for transparent and predictable policymaking to safeguard financial stability. The observable delay in MS propagation provides an opportunity for timely interventions, while the dynamic relationships among SYS, MS, and EPU during crises stress the importance of adaptable and forward-looking policy frameworks. Post-pandemic resilience to macroeconomic shocks, coupled with the sustained influence of EPU, calls for ongoing vigilance and a commitment to maintaining stability through consistent, well-structured policies.

These findings offer valuable insights for policymakers to craft strategies that enhance economic stability, particularly in emerging economies like India, where uncertainties and systemic vulnerabilities can have widespread repercussions.

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