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Portugal

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Rua Miguel Lupi, 20
1249-078 LISBOA
Portugal

Telephone: +351 - 213 925 912
E-mail: rem@iseg.ulisboa.pt

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Stock and sovereign returns linkages: time-varying causality and extreme-quantile determinants[1]

António Afonso[2] José Alves[3] Wojciech Grabowski[4] Sofia Monteiro[5]

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Abstract

We employ a cross-quantilogram approach to assess relationships between quantiles of stock returns and sovereign yields, in the U.S. and Germany, in the period 1990-2024. Specifically, we focus on the lowest 5% quantile of stock returns and the highest 5% quantile of bond returns, providing insights into tail dependencies, crucial during market downturns and periods of heightened volatility. We also measure causality in volatilities extending well-known approaches analyzing volatility transmission. We find significant cross-market relationships between U.S. and German stock and bond markets, influenced by economic crises, macroeconomic dynamics, and monetary policy interventions, and financial stress play a crucial role.

Keywords: stock returns; sovereign bond returns; stock-bond relationship; cross-quantilogram; volatility transmission; US; Germany; monetary policy shocks; fiscal stance
JEL: C32; F21; F37; F42

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[2] ISEG – School of Economics and Management, Universidade de Lisboa; REM – Research in Economics and Mathematics, UECE – Research Unit on Complexity and Economics. CESifo (Center for Economic Studies and Ifo Institute). email: aafonso@iseg.ulisboa.pt
[3] ISEG – School of Economics and Management, Universidade de Lisboa; REM – Research in Economics and Mathematics, UECE – Research Unit on Complexity and Economics. CESifo (Center for Economic Studies and Ifo Institute). email: jalves@iseg.ulisboa.pt
[4] Department of Econometric Models and Forecasts, University of Lodz; ISEG – School of Economics and Management, Universidade de Lisboa; REM – Research in Economics and Mathematics, UECE – Research Unit on Complexity and Economics. email: wojciech.grabowski@uni.lodz.pl
[5] ISEG – School of Economics and Management, Universidade de Lisboa; REM – Research in Economics and Mathematics, UECE – Research Unit on Complexity and Economics. CESifo (Center for Economic Studies and Ifo Institute). email: asmonteiro@iseg.ulisboa.pt

1. Introduction

The dynamic relation between stock and bond markets has been a cornerstone of financial and economic research, given its profound implications for portfolio diversification, risk management, and economic policy formulation. Understanding the nature of these relationships is particularly critical during periods of financial turbulence, when traditional correlation measures often fail to capture the complex interdependencies between asset classes. This study investigates the dynamic interactions between stock and bond markets in two pivotal economies – the United States (U.S.) and Germany (DE). By examining these relationships both within and across these economies, we aim to shed light on the complex interdependencies that characterize these financial instruments under varying market conditions, monetary policy stances, and fiscal environments.

The motivation for this study steams from the need to comprehend market behavior during extreme financial events, where conventional correlation measures of correlation and causality often fall short. Traditional approaches typically focus on mean relationships or linear dependencies, which may obscure critical insights into tail dependencies – those occurring at the extremes of return distributions. Such tail dependencies are particularly relevant during periods of market turmoil, fiscal stress, or heightened volatility, when the relationships between asset classes can exhibit nonlinear and asymmetric behaviors. To address these limitations, we employ the cross-quantilogram methodology, a novel approach that allows for the analysis of lead-lag relationships between different quantiles of stock returns, bond yield changes, and their volatilities. Specifically, we focus on the lowest 5% quantile of stock returns and the highest 5% quantile of changes in sovereign bond yield, providing insights into tail dependencies that are crucial for understanding market behavior during downturns and periods of financial instability.

In the context of the United States, the stock-bond relationship has been extensively analyzed, with findings frequently indicating a negative correlation during periods of economic uncertainty. This phenomenon, often referred to as the flight-to-quality, where investors reallocate capital from stocks to bonds during periods of economic uncertainty (Connolly et al., 2005) However, the magnitude and nature of this relationship can vary significantly depending on the prevailing economic environment and market sentiment (Baker and Wurgler, 2007). Similarly, in Germany, the stock-bond relationship is shaped not only by both domestic factors but also by broader European economic conditions. As the economic linchpin of the Eurozone, Germany's financial markets are closely monitored by investors and policymakers alike. Understanding the dynamics of Germany's stock and bond markets not only provides insights into the country's financial stability but also sheds light on the interconnectedness of European markets (Döpke and Pierdzioch, 2006; Johnson and Soenen, 2009).

Beyond within-country dynamics, this study also explores the cross-country relationships between the U.S. and German stock and bond markets. Given the global integration of financial markets, shocks in one market can disseminate to another, with significant implications for global financial stability.. By analyzing the cross-quantilogram relationships, this research aims to uncover how extreme events in one market can transmit to another, thereby enhancing our understanding of global financial contagion and interdependence (Baur and Lucey, 2009). This is particularly relevant in an era of increasing financial globalization, where the spillover effects of monetary policy, fiscal shocks, and financial stress are amplified across borders.

In addition to examining stock and bond market interactions, we incorporate financial stress indicators, monetary policy shocks, macroeconomic conditions and fiscal stance measures to provide a more comprehensive analysis. Financial stress indicators, such as the Composite Indicator of Systemic Stress (CISS), offer valuable insights into the severity of financial crises and their impact on economic activity (Chavleishvili and Kremer, 2023). Monetary policy shocks, identified through high-frequency data around central bank announcements, reveal the effects of unexpected changes in monetary policy on financial markets (Miranda-Agrippino and Ricco, 2021). Furthermore, we consider the real effective exchange rates on bond and asset returns given its significant influence on financial assets dynamics (Bodart and Reding, 1999; Andersen et al., 2007; Fidora et al., 2007; Viceira, 2012; Valchev, 2020). Lastly, fiscal performance, proxied by the cyclically adjusted primary balance (CAPB), plays a critical role in shaping investor perceptions of sovereign risk and market stability (Ardagna, 2009; Afonso and Sousa, 2011; Centinaio et al., 2024). By integrating these factors, we provide a holistic view of the determinants of stock-bond relationships.

It should be added that to the best our knowledge such in-depth analysis of determinants of causality in extreme quantiles of distribution has not been done before. When we try to evaluate the impact of financial stress, monetary policy shocks, fiscal stance and exchange rates on causality in extreme quantiles of distribution of rates of return, changes in sovereign bond yields, stock market volatilities and bond volatilities, we contribute to the existing literature in stock-bond relationships.

Specifically, our analysis identifies significant patterns in the cross-relationships between stock and bond markets in the U.S. and Germany. In the early 1990s, extreme negative stock returns in the U.S. led to similar movements in Germany, while negative returns in Germany caused opposite movements in the U.S. The 2006-2008 period showed increased interconnectedness during the global financial crisis, and 2018-2020 saw strong bidirectional spillovers coinciding with geopolitical events like the US-China trade war and Brexit.

Further, the European sovereign debt crisis highlighted significant yield spikes and contagion effects, emphasizing the mutual transmission of financial shocks between the U.S. and Germany bond markets. In Germany, the bidirectional relationship between bonds and stocks was positive until the early 21st century, becoming more variable post-2000. During the sovereign debt crisis, heightened volatility caused stocks and bonds to move in opposite directions. In the U.S., the early 2000s showed positive predictability between stock and bond returns, with the 2010s marked by significant cross-asset predictability.

Moreover, exchange rate fluctuations play a moderating role in the short term. When the euro appreciates against the U.S. dollar, causality from the U.S. bond market to the German bond market increases. Conversely, when the euro weakens, causality from the German stock market to the German bond market intensifies. Monetary policy shocks, particularly from the European Central Bank, significantly impact the causality between the German and U.S. bond markets. On the other hand, fiscal primary balances also affects cross-market dynamics, with higher primary balances strengthening the resilience of the German stock market but not the U.S. bond market.

During periods of heightened financial stress, causality from the German stock market to the German bond market decreases, suggesting that German sovereign bonds act as a safe haven. In the U.S., financial stress impacts causality between its bond and stock markets negatively for a one-day lag. Higher financial stress also intensifies causality in volatility.

Our study is organized as follows: Section 2 presents the literature review. Section 3 discusses the employed methodology, data and sources. Section 4 discusses the baseline results and additional conducted robustness checks. Finally, Section 5 summarizes the main conclusions and policy implications.

2. Literature Review

2.1. The relationship between bonds and stocks

The linkages between the returns of stocks and bonds have been deeply analyzed in the literature. Specifically, studies have devoted their efforts to understand the existence of co-movements between these two assets, with empirical evidence of correlation changes between stocks and bonds in different timespans in the last century (Shiller and Beltratti, 1992; Gerrits and Yuce, 1999; Ilmanen, 2003; Jammazi et al., 2015).

Macroeconomic fundamentals have exhibited a significant effect on bonds and stocks trajectories (Yang et al., 2009; Duffee, 2023). For instance, the incorporation of risk and productivity growth, and uncertainty measures to analyze parallel patterns between stocks and bonds have been studied in detail for a long time with different conclusions depending on the variables, economic turmoil and financial stress events, as well as the economies under analysis or financial liquidity (Barsky, 1989; Andersson et al., 2007; Beber et al., 2009; Brière et al., 2012; Chiang et al., 2015; Dufour et al., 2017; Lee, 2021). Moreover, stock market prices are found to play a major role in explaining macroeconomic fundamentals, namely, GDP growth, whilst inflation phenomena are little explained by stock markets evolution (Lee, 1992). Yet, the change between positive and negative correlation among stock and bond prices have been justified with increases in price levels, which lowers bond returns, while higher economic activity leads to an increase in stock prices, therefore, justifying the negative correlation between stocks and bonds in light of a macroeconomic analysis on bond-stocks dynamics (Campbell et al., 2020).

On the other hand, monetary policies are also associated with stock markets dynamics. For instance, an expansionary monetary policy through an unanticipated Federal funds rate cut leads to an increase in stock indexes (Bernanke and Kuttner, 2005). Specifically, Bernanke and Kuttner (2005) found, in their analysis, that the predominant influence on stock price movements is attributable to the effects of unexpected monetary policy actions on anticipated excess returns in the U.S. stock market. However, the monetary policy effects on stock markets are found to be heterogeneous depending on stock markets stage, i.e., if the stock market is in a bearish or bullish regime. In detail, by resorting to modified versions of the Markov-switching model, Chen (2007) demonstrates a significant and negative impact of contractionary monetary policy on stock returns. Furthermore, the findings indicate that the effects of monetary policy are substantially more pronounced during bear-market periods compared to bull-market periods, highlighting two distinct channels through which a tightening monetary policy depresses stock returns: directly lowering returns and increasing the likelihood of transitions to low-return regimes (bear markets).

Furthermore, Grammatikos and Vermeulen (2012) examine the transmission of the 2007-2010 financial and sovereign debt crises to fifteen EMU countries, resorting to daily data from 2003 to 2010 on financial and non-financial stock market indexes. By analyzing stock market returns for three groups within the EMU, namely, North, South, and Small European economies, these authors found that both Northern and Southern European countries experienced significant crisis transmission effects, whereas the smallest countries appeared relatively insulated from international events. Furthermore, the results the authors reach support a robust evidence of crisis transmission to European non-financial sectors from U.S. non-financial sectors, but not for financial sectors, while financial sectors became significantly more sensitive to changes in the spread between Greek and German CDS after the Lehman's collapse, compared to the pre-Lehman Brothers period. However, this increase in sensitivity is much smaller for non-financial sectors. Lastly, prior to the crisis, euro appreciations were associated with declines in European stock markets, a relationship that reversed during the crisis. These conclusions were more recently corroborated by a study conducted by Jammazi et al. (2017).

Beyond the analysis of macroeconomic and monetary policy effects on bond and stock markets, another strand of literature has devoted efforts to comprehend when and why there are, or not, co-movements between the two assets. For instance, Longin and Solnik (2002) investigate the hypothesis that the international equity market correlation increases during volatile periods, a challenging endeavor due to potential spurious relationships between correlation and volatility. They employ extreme value theory to model the tails of multivariate distributions. By deriving the distribution of extreme correlations across various return distributions, the authors provide evidence supporting the rejection of the null hypothesis of multivariate normality for the negative tail, but not for the positive tail. Furthermore, their findings indicate that correlation is more significantly influenced by market trends than by volatility itself, with correlations increasing in bear markets but not in bull markets.

Regarding the co-movements between the stock markets of the U.S. and Germany from January 1980 to September 2002, Bonfiglioli and Favero (2005) do not identify a long-term interdependence between the two markets. However, their empirical findings suggest a short-term interdependence and contagion, wherein short-term fluctuations in U.S. stock prices spill over to German stocks. These co-movements are particularly unstable during episodes of high volatility. Expanding their analysis to encompass G7 countries, Kim and In (2007) employ a wavelet correlation analysis. Their empirical findings indicate that the relationship between fluctuations in stock prices and bond yields varies across different countries and is influenced by the time scale considered. Additionally, the wavelet analysis demonstrates that, with the exception of Japan, changes in stock prices and bond yields generally do not exhibit synchronous movements in most G7 nations. Yet, Ferrer et al. (2016) by making also use of wavelet analysis for European economies found similar conclusions to what Kim and In (2017) reached in their study.

However, Ferrer et al. (2019), by investigating the relationship between long-term bond yields and stock market returns using the quantile-on-quantile method (from January 2001 to March 2016), reveal that the connection between interest rates and equity markets is generally positive. Mainly, the strongest correlations are observed during extreme market conditions, particularly when there are significant drops in 10-year Treasury bond yields and a pronounced bearish trend in stock prices.

Nguyen and Javed (2023) introduce generalized autoregressive score mixed frequency data sampling (GAS MIDAS) copula models to examine the dynamic relationship between stock and bond returns, which are essential for portfolio allocation and risk management and to split the analysis into short-term and long-term dependencies, and also to consider asymmetric dependencies at different quantiles. Therefore, while the long-term dependence is influenced by macro-financial factors through a MIDAS regression, the short-term dependence is modeled using a GAS process, highlighting the relevance of this methodological approach under an optimizing portfolio allocation perspective, and enhancing risk management accuracy.

On the other hand, Baur and Lucey (2009) investigate the phenomenon of investors switching between stocks and bonds, proposing definitions and tests for flight-to-quality, flight-from-quality, and cross-asset contagion. By examining these dynamics, the authors explore their results' implications for the financial system. An empirical analysis of eight developed countries, including the U. S., U. K., Germany, and Japan, reveals that such flights are prevalent during crises and not confined to individual countries but occur simultaneously across multiple nations. This suggests a connection between these flights and cross-country contagion, at the same time, such flights contribute to the resilience of financial markets by offering diversification benefits during periods of heightened uncertainty. Conversely, Adrian et al. (2019) identify a significant and nonlinear relationship between stock and bond returns and historical equity market volatility, as assessed by the Chicago Board Options Exchange Market Volatility Index (VIX). They develop a novel estimator that utilizes variations in cross-sectional returns to capture this relationship. Their analysis reveals that the nonlinear patterns for stocks and bonds are inversely correlated, illustrating a flight-to-safety effect: as volatility escalates from moderate to high levels, expected returns for stocks increase, while those for Treasury bonds decrease. These findings bolster dynamic asset pricing models that propose the risk premium is a nonlinear function of market volatility.

Lastly, intra-week seasonality plays an important role in the relationship between stocks and bonds. For instance, Flannery and Protopapadakis (1988) examined the persistence of intra-week seasonality in stock and bond markets, focusing on three stock indices and Treasury bonds with seven different maturities. Their research reveals that intra-week seasonality remains significant but exhibits varying patterns across both asset classes and among the different bond maturities. Notably, they observe that Monday returns tend to become more negative as bond maturity increases, a trend seen in both stocks and bonds. These results imply that neither institutional factors nor general-equilibrium theories alone can fully account for the observed intra-week seasonal patterns in the securities markets. In a more recent study, Cho et al. (2007) investigate the Monday effect in daily stock index returns using the stochastic dominance criterion, which is a more robust measure compared to the mean comparison methods used in earlier research. As justified by the authors, this criterion enables a clearer economic interpretation of the obtained results. The findings reveal strong evidence of the Monday effect in many instances under this stringent criterion. While the effect has diminished or reversed in the Dow Jones and S&P 500 indices since 1987, it remains pronounced in broader indices like the NASDAQ, Russell 2000, and CRSP (Center for Research in Security Prices) indices.

When assessing the relationship between stock and bond market, as in the case of the analysis for pairs of stock markets and pairs of bond markets, the problem of volatility transmission is also important. Chuliá and Torró (2008) analyzed volatility spillovers among European stock and bond markets, indicating that volatility spillovers in both directions and that the stock-bond trading rules offer profitable returns. Dean et al. (2010) documented asymmetry in the mechanism of volatility transmission between stock and bond market. The results for these two segments of the Australian financial market indicated that in the period 1992-2006 bond market volatility spilled over into the equity market, but the reverse was not true. Moreover, the transmission of bond market volatility into stock market volatility depended on signs of the return shocks in each market.

As Reinhart and Rogoff (2008) indicate, during crises, financial market volatility increases sharply and spills over across markets. Motivated by such considerations Diebold and Yilmaz (2012) introduced a volatility spillover measure based on forecast error decompositions from the VAR model. They analyzed volatility spillover among various asset classes including stocks and bonds. The analysis of volatility spillovers for stock-bond pairs indicated net positive volatility spillovers from stock market to bond market during the Global Financial Crisis, as well as in the years 2002-2003. Hence, this means that positive net transmission from the stock to the bond market was recorded in periods of heightened financial stress, while positive net transmission in the opposite direction was observed in tranquil times. In opposition to Diebold and Yilmaz (2012), Baruník and Křehlík (2018) proposed the analysis of volatility transmission in frequency domain. In addition, Tiwari et al. (2018) have shown that stock and CDS markets are net transmitters of volatility and degree of connectedness increases at higher frequency.

While previous literature has explored the relationship between stocks and bonds, it exhibits several limitations. Notably, much of the existing research does not examine extended time horizons, such as the one adopted in this study, which spans multiple crises. Furthermore, many empirical studies are constrained by the use of narrow and less comprehensive methodologies. These approaches often fail to account for the various quantiles of the distribution and their cross-predictability, instead focusing solely on the entire distribution or its upper extremes. Additionally, prior research has predominantly centred on returns, overlooking the valuable predictive insights that can be derived from volatilities. Finally, a significant portion of the literature emphasizes the U.S. market, often neglecting other influential markets, such as Germany.

2.2. Cross-Quantilogram

In economic and financial research, the issue of predictability is of paramount importance (Cowles and Jones, 1937). In line with this, numerous methodologies based on sign or rank statistics have been proposed, namely by Dufour et al. (1998), Christoffersen and Diebold (2002), among others.

One of such developments is the quantilogram approach introduced by Linton and Whang (2007), a tool for measuring predictability across different parts of the distribution of a stationary variable, based on the correlogram of "quantile hits". The authors applied a test for the hypothesis that a given time series exhibits no directional predictability. The null hypothesis posited by Linton and Whang (2007) asserts that the past information set of the stationary time series $\{y_t\}$ does not enhance the prediction of whether $\{y_t\}$ will fall below or above the unconditional quantile. Moreover, Han et al. (2016) argue that the quantilogram offers significant advantages over other test statistics for directional predictability, being conceptually appealing and easier to interpret. Additionally, the quantilogram approach is effective for heavy-tailed series, which are common in financial high-frequency data, as well as has the ability to consider very long lags, compared to regression-type methods, another notable advantage of the quantilogram.

This methodology has been extended by several authors, such as Davis and Mikosch (2009) who have introduced the extremogram, which applies the quantilogram to extreme quantiles. On the other hand, Davis et al. (2012) proposed statistical inference methods based on bootstrap and permutation for the extremogram. Further extensions include the work of Davis et al. (2013) who considered the quantilogram within a Fourier domain.

More recently, Han et al. (2016) proposed the cross-quantilogram to measure quantile dependence between two series, advocating statistical inference to test the hypothesis that one time series does not exhibit directional predictability over another. The authors established the asymptotic distribution of the cross-quantilogram and applied a stationary bootstrap procedure based on Politis and Romano (1994), to construct consistent confidence intervals. Furthermore, Pham (2021) highlighted the significant advantages of the cross-quantilogram, noting its robustness to misspecification errors and its flexibility in handling long lags compared to standard linear regression models. Additionally, the cross-quantilogram allows for the evaluation of directional transmission strength over different time periods without relying on movement conditions. The attributes of this methodology enhance its robustness for analysing the relationship both between and within stocks and bonds, making it well-suited for the objectives of our study.

Empirical applications of the cross-quantilogram have predominantly focused on financial markets, particularly high-frequency data. Han et al. (2016) addressed stock return predictability, applying the cross-quantilogram to detect directional predictability from economic state variables to stock returns. The authors demonstrated that the cross-quantilogram provides a more comprehensive relationship between predictors and stock returns. Another application by Han et al. (2016) involved analyzing the systemic risk of individual financial institutions.

The cross-quantilogram has also found popular applications in ecological finance. Empirical research has explored topics such as decarbonization and green bonds. For example, Uddin et al. (2019) examined cross-quantilogram-based correlation and dependence between various asset classes and renewable energy stock returns, indicating a positive dependence of renewable energy stock returns on other asset returns, though this relationship did not hold when return series were in opposite quantiles. Pham (2021) evaluated the connectedness between green bonds and green equity across different investment horizons and market conditions, finding stronger connectedness during extreme market conditions. Razzaq et al. (2022) tested directional predictability between carbon trading and sectoral stocks in China using the cross-quantilogram. The study revealed an asymmetric dependence structure between carbon trading prices (CTP) and sectoral stocks, identifying negative directional predictability from CTP to stock market prices in bullish markets and positive predictability in bearish markets. Zhang et al. (2023) investigated whether the connectedness among fossil energy returns impacts renewable energy stock returns, concluding that only in extreme events such as the Global Financial Crisis, there is an interconnection between renewable and non-renewable energy markets.

The cross-quantilogram has also proven to be an effective statistical method for analyzing dependence between financial technology stocks and other asset classes. For instance, Karim et al. (2023) identified an asymmetric relationship between climate policy uncertainty and energy metals, using quantile causality and dependence analysis between financial technology stocks, green financial assets, and energy markets. Their study found that fintech prices were highly directionally predictable in all markets except green bonds in the lower quantiles of distributions, with negative predictability across all lag lengths in bullish states. Abakah et al. (2023) analyzed the distributional and directional predictabilities among fintech, bitcoin, and artificial intelligence stocks, finding that directional predictability among different assets was oscillatory over time lags, with stronger price connectedness for highly positive and negative changes.

Further applications of the cross-quantilogram have explored the relationship between stock market returns and other markets or indices. For instance, Kumar et al. (2021) utilized the cross-quantilogram to analyze the relationship between oil prices and stock market returns, investigating whether the inclusion of the geopolitical risk variable enhances the directional predictability from oil to stock returns. Their in-depth analysis differentiated between oil-exporting and oil-importing countries, revealing that the response of oil-exporting markets to energy shocks was higher and more persistent compared to oil-importing ones. Additionally, when the dependence structure of oil prices with stock markets was examined without accounting for geopolitical risk, no significant dependence was identified. However, upon conditioning for geopolitical risk factors, Kumar et al. (2021) found evidence of positive quantile dependence when both oil and stock returns were in the same quantiles of the distribution.

Lastly, Dai et al. (2022) analyzed cross-quantile dependence between the Chinese stock market, Chinese commodity market, crude oil, and investor sentiment. They identified a substantial degree of spillover among various Chinese commodity futures, a significant increase in total system spillover during major financial crises and the COVID-19 pandemic, and a high persistence of positive correlation between the stock index and investor sentiment index. Yet, Chang et al. (2024) employed data from the Taiwan Stock Exchange Weighted Index and the New Taiwan Dollar. Using the cross-quantilogram approach, they supported the flow-oriented hypothesis, demonstrating a negative Granger causality relationship from the New Taiwan Dollar to the Taiwan stock market, although this phenomenon persisted for only one day.

3. Methodology and Data

This section outlines the methodological approach implemented to perceive the relationship between bonds and stocks of the U. S. and Germany. Subsequently, we present the empirical strategy and the data.

3.1. Quantilogram setup

Assuming that $(\boldsymbol{y}_t, \boldsymbol{x}_t, t \in Z)$ are a strictly stationary time series with $\boldsymbol{y}_t = (y_{1t}, y_{2t})^T \in R^2$ and $\boldsymbol{x}_t = (x_{1t}, x_{2t}) \in R^{d_1} \times R^{d_2}$, where $x_{it} = \left[x_{it}^{(1)} \quad \cdots \quad x_{it}^{(d_i)}\right]^T \in R^{d_i}$ with $d_i \in N$ for i=1,2. Let $F_{y_{i|x_i}}(\cdot\ |x_{it})$ denotes the conditional distribution function of the series y_{it} given x_{it} and $f_{y_{i|x_i}}(\cdot\ |x_{it})$ denotes appropriate density function. Han et al. (2016) defined cross-quantilogram on the basis of the conditional quantile function defined as $q_{i,t}(\tau_i) = inf\left\{v: F_{y_{i|x_i}}(v|x_{it}) \geq \tau_i\right\}$ for $\tau_i \in (0,1)$, for i=1,2.

The cross-quantilogram is a measure of serial dependence between two events $\{y_{1t} \leq q_{1,t}(\tau_1)\}$ and $\{y_{2t-k} \leq q_{2,t}(\tau_1)\}$ for any pair $\tau = (\tau_1, \tau_2)^T \in \mathcal{T}$ and for an integer k, where $\mathcal{T}$is the range of quantiles someone is interested in evaluating directional predictability. Since $\{y_{it} \leq q_{i,t}(\cdot)\}$ is called the quantile-hit or quantile-exceedance process (Linton and Whang, 2007), the cross-quantilogram is defined as the cross-correlation of the quantile hit processes:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau_1}\left(y_{1t}-q_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2t-k}-q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau_1}^2\left(y_{1t}-q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau_2}^2\left(y_{2t-k}-q_{2,t-k}(\tau_2)\right)\right]}}, \qquad (1)$$

for $k = 0, \pm 1, \pm 2, \dots$, where $\psi_a(u) = 1[u < 0] - a$.

In general, the cross-quantilogram is an extension of the quantilogram proposed by Linton and Whang (2007). While the quantilogram measures correlation between quantile-hit processes for a single time series, the cross-quantilogram captures serial dependence between the two series at different (or the same) conditional quantile levels.

The null hypothesis in the cross-quantilogram is:

$$H_0: \rho_\tau(1) = \rho_\tau(2) = \cdots = \rho_\tau(k) = 0 \qquad (2)$$

against the alternative hypothesis:

$H_1: \rho_\tau(k) \neq 0$ for some k.

In order to test this hypothesis, Han et. al. (2016) proposed the following Ljung-Box statistic:

$$Q_\tau^*(p) = T(T+2)\sum_{k=1}^{p} \hat{\rho}_\tau^2(k)/(T-k), \tag{3}$$

and the sample cross-quantilogram $\hat{\rho}_\tau^2(k)$ is calculated according to the following formula:

$$\hat{\rho}_\tau^2(k) = \frac{\sum_{t=k+1}^{T} \psi_{\tau_1}\left(y_{1t}-\hat{q}_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2t-k}-\hat{q}_{2,t}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\psi_{\tau_1}^2\left(y_{1t}-\hat{q}_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi_{\tau_2}^2\left(y_{2t-k}-\hat{q}_{2,t}(\tau_2)\right)}}. \tag{4}$$

After calculating the values of the cross-quantilogram, the impact of financial stress index, monetary policy surprise shocks, fiscal stance and exchange rate are also studied. Hence, the values of the cross-quantilogram for sub-periods $s=1,\ldots,S$ are regressed on values of financial stress index, monetary policy shocks, fiscal primary balance and exchange rate. In addition, the vectors of the dependent and of the explanatory variable are defined for non-overlapping sub-periods of 18 months[6]. Specifically, we consider the following relationship:

$$CQ_s = f\left(FSI_s, MPS_s^{ECB}, MPS_s^{Fed}, CAPB_s^{DE}, CAPB_s^{US}, EXRATE_s^{DE\_US}, \varepsilon_s\right). \tag{5}$$

The vector $EXRATE_s^{DE\_US}$ consists of two variables: $REER_s^{DE}$, the real effective exchange rate for Germany and $REER_s^{US}$, the real effective exchange rate for the U. S., or another variable $EXRATE_s^{USD/EUR}$, i.e., the bilateral exchange rate between USD and EUR. *FSI* is the Financial Stress Index, MPS_s^{ECB} and MPS_s^{Fed} are the monetary policy surprise shocks of the European Central Bank (ECB) and the United States Federal

[6] It should be stressed that the values of the cross-quantilogram measure presented in Tables 2-4, and A1-A3, in the Appendix, are calculated for overlapping windows. The choice of the 3-year rolling window enables an analysis of the cross-quantilogram measures for a sufficient number of observations and an analysis of the time-varying directional predictabilities for short periods. However, in the case of the regression model, the use of non-overlapping windows seems to be more appropriate. The longer is the sub-period (the cross-quantilogram is measured with higher precision), the shorter is the sample considered in the regression model explaining directional predictability in extreme quantiles. Using non-overlapping 18-months subperiods is a trade-off between the precision of estimation of the cross-quantilogram and the precision of estimation of a regression model.

Reserve (Fed), respectively. $CAPB_s^{DE}$ and $CAPB_s^{US}$ are the cyclically adjusted primary balances, CAPB, for Germany and the United States, respectively.

3.2. Empirical Strategy

To comprehensively analyze the relationship between stocks and bonds in the United States and Germany, we examine the rates of return, changes in yields, and volatilities across one, two, and three-day lags for both countries, given the weak seasonality effects on the financial markets (Flannery and Protopapadakis, 1988; Cho et al., 2007). Our analysis encompasses stock-stock and bond-bond interactions between the United States and Germany, as well as stock-bond interactions within each economy. To achieve robust results, it is imperative to select the most appropriate econometric models. The selection process requires identifying the order of integration of the variables included in the model. Although the cross-quantilogram values are computed based on stationary data, the time series of these values, which reflect causality performance over extended periods, may exhibit non-stationarity due to temporal changes. Similarly, exchange rates are expected to display non-stationarity. Hence, the cross-quantilogram values for stock market returns and changes in yields are calculated for various scenarios based on the following dimensions:

1. Between the U.S. and Germany stock markets, between U.S. and Germany bond markets, and between stock and bond markets within both countries, resulting in four variants;
2. For different daily lags, i.e., one, two, and three-day lags (1, 2, 3), totaling three variants;
3. In both directions, changing causes and effect results in two variants.

Ultimately, we then obtain a total of 24 time series (4*3*2) reflecting causality. However, we also consider the cross-quantilogram values for volatilities in both directions, between stock market volatilities, between bond market volatilities and both stock and bond market volatilities within both countries. Eventually, we obtain 8 (4*2) more time series reflecting causality, so finally we have 32 time series. Naturally, stationarity may be present in some series, while absent in others. For the series where causality measures are integrated of order 1, we aim to identify long-run and short-run determinants using an error correction model. Conversely, for stationary causality measures, we estimate the parameters of standard linear regression with the first differences of explanatory variables integrated of order 1.

In the case of non-stationary causalities, we estimate the following Error Correction Model:

$$\Delta CQ_s = (\alpha_1 - 1)\left(CQ_{s-1} - x_{s-1}\hat{\lambda}\right) + z_s\mu + \varepsilon_s, \tag{6}$$

where the vector x_{s-1} consists of other I(1) variables, $\hat{\lambda}$ is the vector of estimates of the cointegrating relationship and vector $\boldsymbol{z}_s$ consists of stationary variables and first differences of I(1) variables.

An additional comment should be made regarding the strategy for handling low values of the cross-quantilogram that do not significantly differ from zero. We treat these values as non-zero for several reasons. The econometric methods suitable for identifying determinants of limited dependent and qualitative variables perform well with a large number of observations (see Maddala, 1983; Amemiya, 1985), which are typical in microeconomic analyses. In fact, models for limited dependent and qualitative variables, applied to time series generated by stochastic processes integrated of order 1, require an adequate number of observations (Grabowski and Welfe, 2016, 2020). Although we use daily data spanning from 1990 to mid-2024, the time series reflecting causality are calculated for non-overlapping windows. To obtain reliable results, these windows cannot be too narrow, which reduces their number. Furthermore, in the Tobit model (Tobin, 1958), we have an equation for the unobservable variable y_t^*, for which we know it is negative if the observable y_t equals zero. In our case, we have precise values of the cross-quantilogram measure, even if they are very low, providing additional information compared to the Tobit model. This means our case differs from the traditional cases considered by Tobin (1958), where the observable expenditures for durable goods were zero.

3.3. Data

This study uses data for Germany and for the U. S. for the period between 02/01/1990 and 28/06/2024. Our key variables of interest are the stock returns calculated based on DAX 40 and S&P 500, the bond returns calculated on the 10-year German bond yields and the 10-year U.S. bond yields, as well as the realized volatilities of both stocks and bonds. Data on these variables was retrieved from Thomson Reuters Datastream.

To analyze the impact of financial stress on time-varying causality among rates of return and volatilities we use data on the Financial Stress Index, which is available on FRED Database since 1990.[7] Once the values of the cross-quantilogram in the bad stance of financial markets are explained, measures of the Financial Stress Indicator should also reflect bad stance of financial markets. The higher value of the Financial Stress Index informs about stronger stress in financial markets. Therefore, in each case the quantile of order 0.95 is taken as an explanatory variable.

Data concerning the monetary policy surprises of the Fed and of the European Central Bank (MPS_s^{Fed} and MPS_s^{ECB}, respectively) are taken based on the research conducted by Jarociński and Karadi (2020). It should be stressed that data related to the monetary policy surprises of the European Central Bank have been available since 2000. Therefore, for the estimations in the second step, in that case, we considered that time span.

Lastly, for the second stage estimations, we included the cyclically adjusted primary balance of Germany and of the U.S. as percentage of GDP for the period between 1991 and 2023 ($CAPB_s^{DE}$ and $CAPB_s^{US}$), retrieved from the Bundesbank and the International Monetary Fund, respectively. Additionally, we have included the Real Effective Exchange rate of Germany and the U.S.as well as the Exchange rate of USD/EUR, collected from the BIS database between 1991 and 2023 ($REER_s^{DE}$, $REER_s^{US}$ and $EXRATE_s^{USD/EUR}$).

In our empirical research, we analyze two distinct temporal dimensions. The first dimension utilizes daily data (five-day workweek) spanning from January 1990 to June 2024. The second dimension involves a time series observed at an 18-month frequency. Specifically, we have the following windows: the initial observation captures the performance of causality to other variables from January 1990 to June 1991, the second observation reflects the performance in the period between July 1991 and December 1992,…, and the last observation reflects the performance in the period between January 2023 and June 2024. The values of the causality measure, specifically the cross-

[7] Typically, the Financial Stress Index is extracted from the website https://www.financialresearch.gov/financial_stress_index/. However, data is only available since 2000. Therefore, with the use of the relationship between Financial Stress Index and Kansas City Financial Stress Index, estimates of values of the FSI for years 1990-1999 are used.

quantilogram, are computed within these windows. Correspondingly, the other variables are adjusted to ensure that their values are recorded within the same 18-month intervals.

In the case of the monetary policy shocks, the variables MPS_s^{ECB} and MPS_s^{Fed}, their values are also aggregated in windows, since they take non-zero daily values at days of meetings devoted to changes of policy rate at the European Central Bank and the Fed.

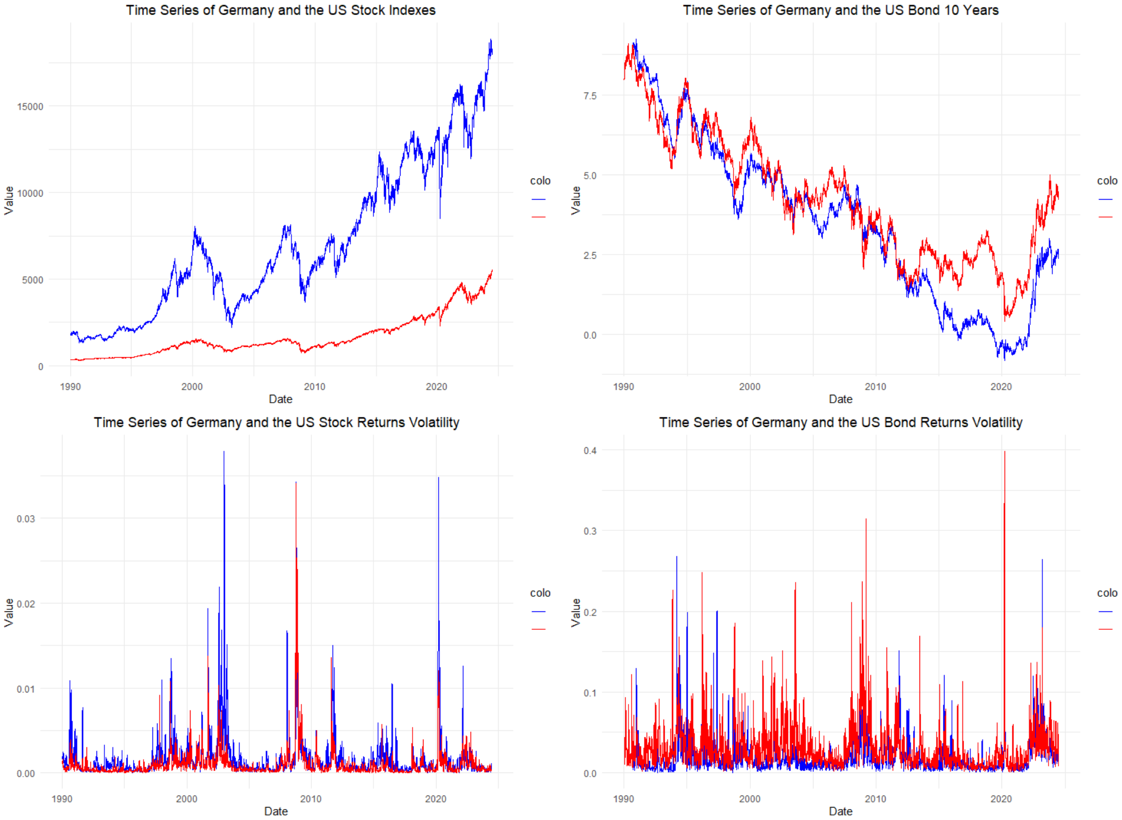
Regarding the observations of for the $CAPB_s^{DE}$ and for $CAPB_s^{US}$ they were extracted on a yearly frequency and transformed into 18-monthly frequency, in a such way that the value for a given year is multiplied by (2/3) if the whole year constitutes a window and multiplied by (1/3) if half of a year constitutes a window. For example, if we calculate the $CAPB_s^{DE}$ for a window between January 1990 and June 1991, we multiply the value of this variable from 1990 by (2/3), and for the values of this variable from 1991 we multiply them by (1/3). On the other hand, when we calculate the value of the $CAPB_s^{US}$ for a window between July 1991 and December 1992, its value from 1991 is multiplied by (1/3) and its value from 1992 is multiplied by (2/3).

Lastly, in the case of exchange rate variables ($REER_s^{DE}$, $REER_s^{US}$ and $EXRATE_s^{USD/EUR}$) monthly data from the end of months were downloaded. Therefore, the average values for 18-months are calculated for all windows and these values are used in the econometric model explaining time-varying causality.

In Figure 1, we present four graphical representations illustrating the evolution of Germany (blue) and the U.S. (red) Stock Indexes, 10-year bond yields, and the volatilities of stocks and bonds returns, from 1990 to 2024. The data clearly indicates that German stock indexes have experienced significantly higher growth compared to their U.S. counterparts, particularly in recent years. However, this growth is accompanied by notably higher return volatility in Germany over the period analyzed.

In terms of bond yields, the trajectories for both countries display a similar downward trend, closely mirroring each other. Despite this parallel movement, U.S. bond yields consistently exhibit slightly higher values relative to German bonds.

Figure 1: Summary representations of Germany and the U.S.



Notes: This figure displays four graphical representations of the evolution of Germany (blue) and the U.S. (red) Stock Indexes, Bond 10 years yields, and Stocks and bonds returns volatilities, between 1990 and 2024. Source: Author's own calculations.

Table 1. Descriptive statistics of the daily data.

	Mean	*Median*	*Std. Dev.*	*Min.*	*Max.*	*Obs.*	*Skewness*	*Kurtosis*
Bonds US	-0.0004	-0.0018	0.0602	-0.5220	0.4370	8998	0,1541	6.1283
Bonds Germany	-0.0007	-0.0010	0.0466	-0.3880	0.3550	8998	-0,0146	6.8782
Stocks Returns US	0.0003	0.0007	0.0109	-0.0911	0.1014	8998	-0,2399	10.6329
Stocks Returns Germany	0.0003	0.0007	0.0139	-0.1038	0.1387	8998	-0,2521	9.4747
Volatility Stock Returns US	0.0011	0.0005	0.0019	0.0000	0.0341	8998	7,1779	79.5518
Volatility Stock Returns Germany	0.0017	0.0009	0.0029	0.0000	0.0379	8998	5,5867	48.3735
Volatility Bonds US	0.0327	0.0232	0.0318	0.0012	0.3982	8998	3,5771	24.2267
Volatility Bonds Germany	0.0196	0.0124	0.0225	0.0000	0.2685	8998	4,1657	31.5184
FSI_s	0.6516	0.2412	1.3420	-0.6905	5.6964	23	2.3333	9.6913
MPS_s^{Fed}	-0.1413	-0.0798	0.3237	-0.9108	0.2716	23	-1.2187	3.6631
MPS_s^{ECB}	0.0424	0.0589	0.1604	-0.2890	0,4227	17	0,1165	4.0001
$CAPB_s^{US}$	-2.3697	-2.5226	2,4401	-5,4150	1,3029	23	0,2153	1.4322
$CAPB_s^{DE}$	0.2300	0.0794	0.9496	-1.9181	1.6858	23	-0.1495	2.4682
$REER_s^{US}$	87.2131	84.8333	9.1338	76.5444	104.1456	23	0.5059	1.8495
$REER_s^{DE}$	102.5884	101.0939	3.9906	96.4817	113.2556	23	0.9981	3.5741
$EXRATE_s^{DE\_US}$	0.8524	0.8324	0.0976	0.7045	1.1176	23	0.8357	3.7058

Notes: This table displays a summary statistic (Mean, Median, Standard Deviation, Minimum, Maximum, number of observations, Skewness, and kurtosis of all variables employed in this study for the period of 1990 to 2024. Source: Author's own calculations.

Table 1 provides the summary statistics for all variables used in this study. Notably, the table highlights the negative bond returns observed, as well as the similarities between German and U.S. stock returns. However, it is evident that German stock returns and U.S.

bond returns exhibit high volatility. Additionally, the presence of more extreme deviations from the mean are reported for U.S. stock returns and German bond return volatilities.

4. Empirical Analysis

4.1. *Baseline Results*

4.1.1. Returns

Initially, we investigate the relationships between stock market returns and fluctuations in 10-year sovereign bond yields for the United States and Germany, across various quantiles of the distribution, using data from 1990 to mid-2024.

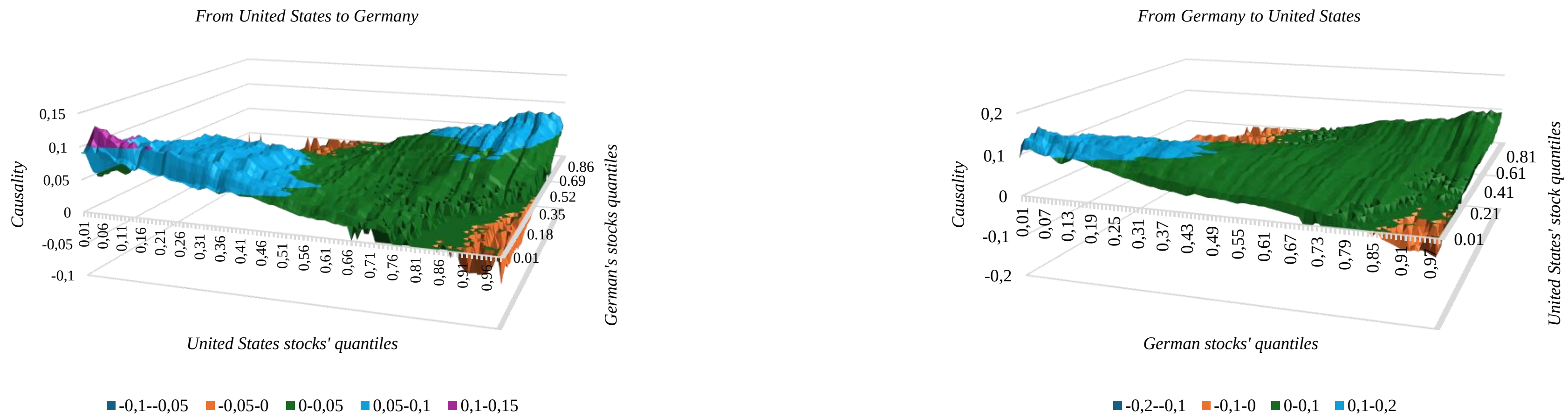
Figure 2 illustrates the causality relationship between U.S. and German stock returns quantiles with a one-day lag. The left chart of Figure 2, which depicts U.S. stock returns causing German stock returns across different quantiles, highlights a positive and stronger causality, particularly when the analysis focuses on the highest quantiles of stock returns. Simultaneously, the lowest returns of U.S. stock markets exhibit a stronger causality, in the same direction, with German stock market returns. This pattern is consistent when explaining U.S. one-day-ahead stock returns caused by German stock markets (Figure 2, right chart). Specifically, lower returns, depicted by the lowest quantiles, correspond to lower returns in the other market on the following day.

While the negative returns between markets are more synchronized in their causality (as seen in both charts of Figure 3 for the lowest stock returns quantiles), the relationship in the highest stock returns quantiles shows less synchronization between the two markets. Additionally, a pattern emerges relating opposite extreme quantiles of stock returns between the United States and Germany. Specifically, the lowest (highest) stock return quantiles in the U.S. tend to cause higher (lower) returns in German stock markets. The same rationale is observed when the German market causes the stock returns in the U.S. stock market on the following day, consistent with the findings of Bonfiglioli and Favero (2005) on the co-movements between U.S. and German stock markets.

Figure 4 demonstrates that the bidirectional predictability between the quantiles of German bonds and U.S. bonds exhibits a similar relationship to that observed in Figure 3. However, across quantiles, the degree of causality is more uniform from the United States to Germany. Notably, for the top quantiles of bond returns from the source market (United States in the left chart, Germany in the right chart), there appears to be a reduction in returns in the following day in the sovereign debt market of the other country. This behavior may indicate a flight to safety, as higher bond returns correspond to lower bond prices, signaling increased risk. Consequently, financial investors may deleverage their positions and allocate investments to safer markets, whose behavior is consistent with the nonlinearity and flight-to-safety in the risk-return trade-off for stocks and bonds (Adrian et al., 2019).

When examining the cross-relationship between stocks and bonds, we observe that the strongest causality persists at the extremes of the quantiles for Germany and the United States, as depicted in Figures 4 and 5, respectively. However, these causal relationships are weaker compared to those observed between stocks-stocks and bonds-bonds. Furthermore, Figures 4 and 5 illustrate that the cross-quantile relationship from bonds to stocks is more heterogeneous, whereas the causality from stocks to bonds is more homogeneous and approaches a non-significant relationship (with causalities varying between -0.05 and 0.05). Even within the stock-to-bond causality relationships, the United States emerges as a more dynamic case of stock-to-bond causality. These observations are consistent with the findings of Baur and Lucey (2009), who analyzed flights to quality and contagion in stock-bond correlations, thereby providing further support for the observed patterns.

Figure 2. Values of cross-quantilogram indicating directional predictability between stock markets with 1-day lag.

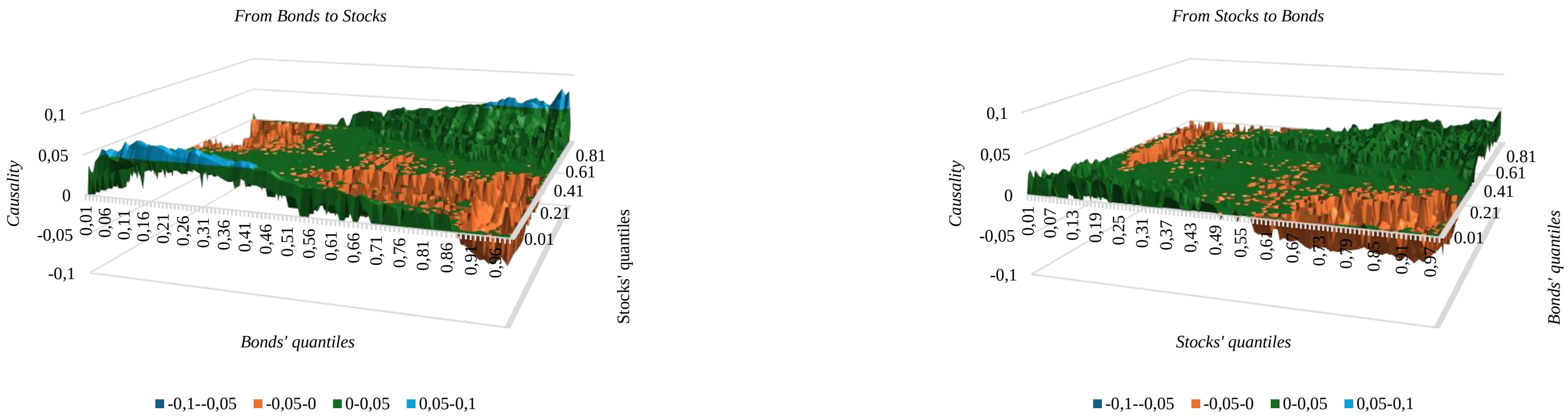


Source: Authors' calculations.

Figure 3. Values of cross-quantilogram indicating directional predictability between bond markets with 1-day lag.

Source: Authors' calculations.

Figure 4. Values of cross-quantilogram indicating directional predictability between stock and bond market for Germany (1-day lag).



Source: Authors' calculations.

Figure 5. Values of cross-quantilogram indicating directional predictability between stock and bond market for the U.S. (1-day lag).

Source: Authors' calculations.

4.1.2. Volatilities

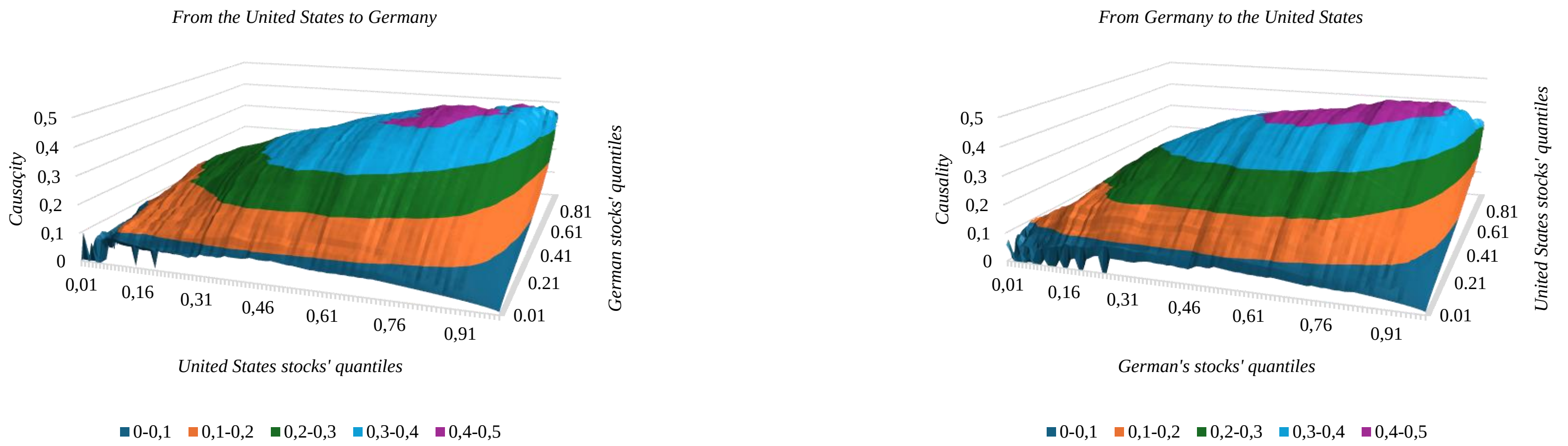
In this subsection, we examine the predictability of volatilities in the stock and bond markets of Germany and the U.S. From Figures 6 and 7, we can see that causality between the S&P 500 and the DAX 40 stock and bond returns volatilities is not uniformly distributed across quantiles. At lower quantiles (0.0 to 0.01), the causality measures are minimal, indicating little influence of low S&P 500 volatilities on DAX 40 volatilities, and vice versa. However, as the quantiles increase, there is a noticeable rise in causality measures, illustrating that cross-country predictability is more pronounced in the upper quantiles of both stocks and bonds, exhibiting a smooth inclined surface across the quantiles. Additionally, cross-country predictability in stocks (from the U.S. to Germany and vice versa) shows the highest coefficients, ranging between 0.4 and 0.5, indicating a strong predictive relationship.

Regarding cross-asset predictability, Figures 8 and 9 also reveal an upper slope surface towards the upper quantiles, although it is less smooth and smaller compared to Figures 6 and 7. Specifically, certain mid-range quantiles of the German bond yields (around 0.50 to 0.70) in Figure 8 exhibit sporadic spikes in causality measures, affecting specific quantiles of the DAX 40 stock returns. These irregularities suggest that there are complex dynamics at play, possibly influenced by market-specific events or broader economic factors that affect both bond and stock markets differently at various volatility levels.

In the case of the U.S., we can observe in Figure 9 that the unidirectional relationship between bonds to stocks presents a similar pattern throughout all quantiles of the distribution, with a relative spike in the highest quantiles.

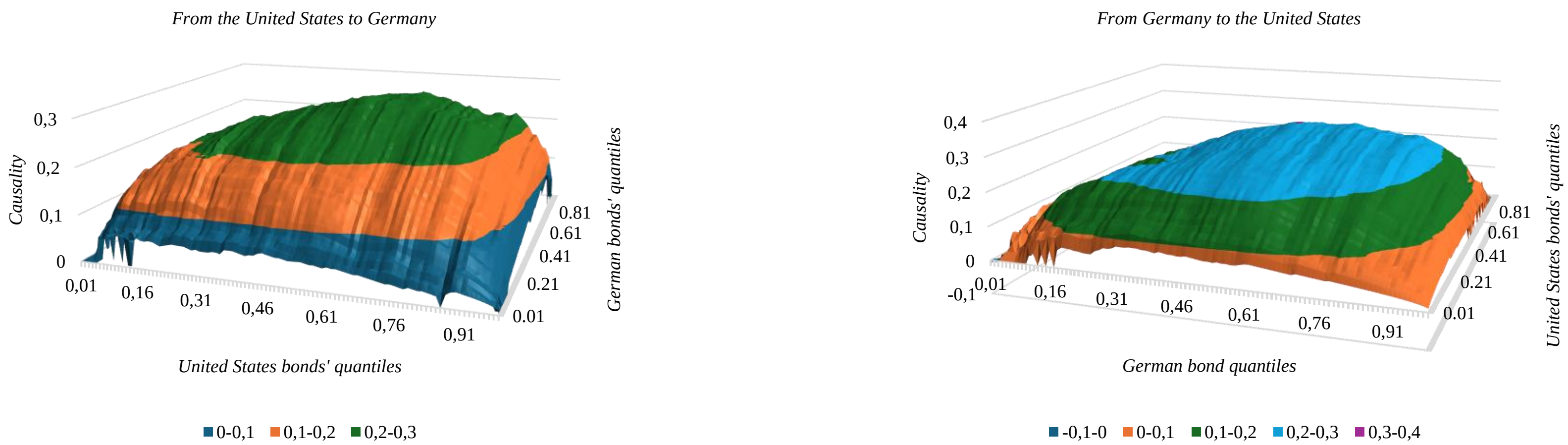
In conclusion, the causality analysis between the volatilities of changes in yields of United States and Germany sovereign bonds and the volatilities of S&P 500 and DAX40 stock returns demonstrates a clear dependency, particularly at higher volatility levels. The findings underscore the importance of considering volatility quantiles when assessing market interdependencies, as the impact is not uniform across different volatility levels. Specifically, for highly turbulent periods in financial markets, when typically, financial assets vary the most, they show some degree of mutual influence. This nuanced understanding can aid in better risk management and forecasting in financial markets, providing valuable insights for investors and policymakers.

Figure 6. Values of cross-quantilogram indicating directional predictability between stock market volatilities with 9-days lag.



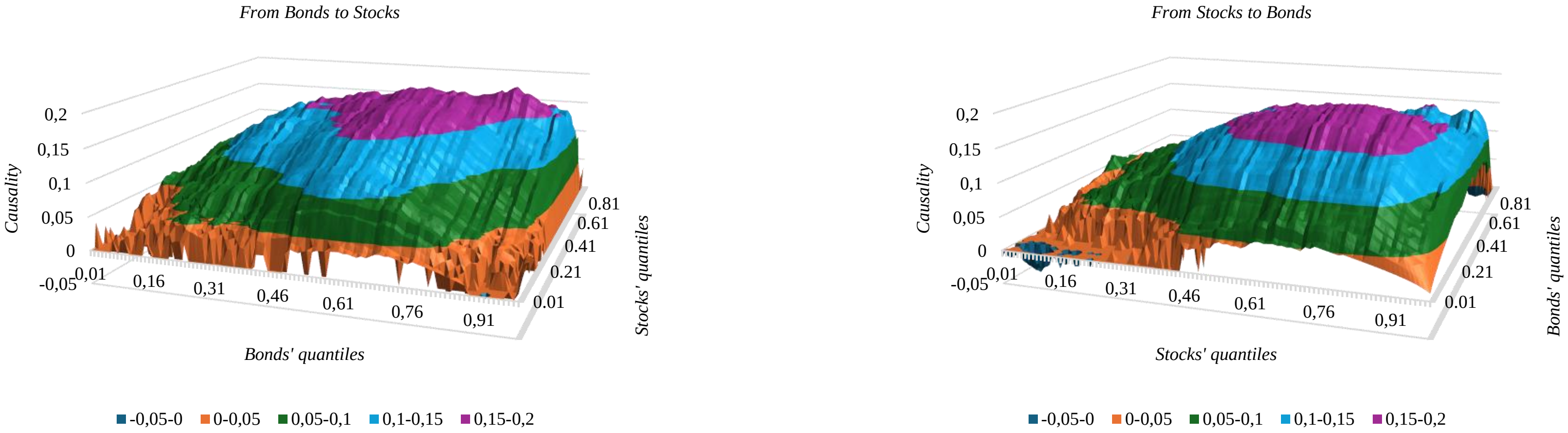
Source: Authors' calculations.

Figure 7. Values of cross-quantilogram indicating directional predictability between bond market volatilities with 9-days lag.



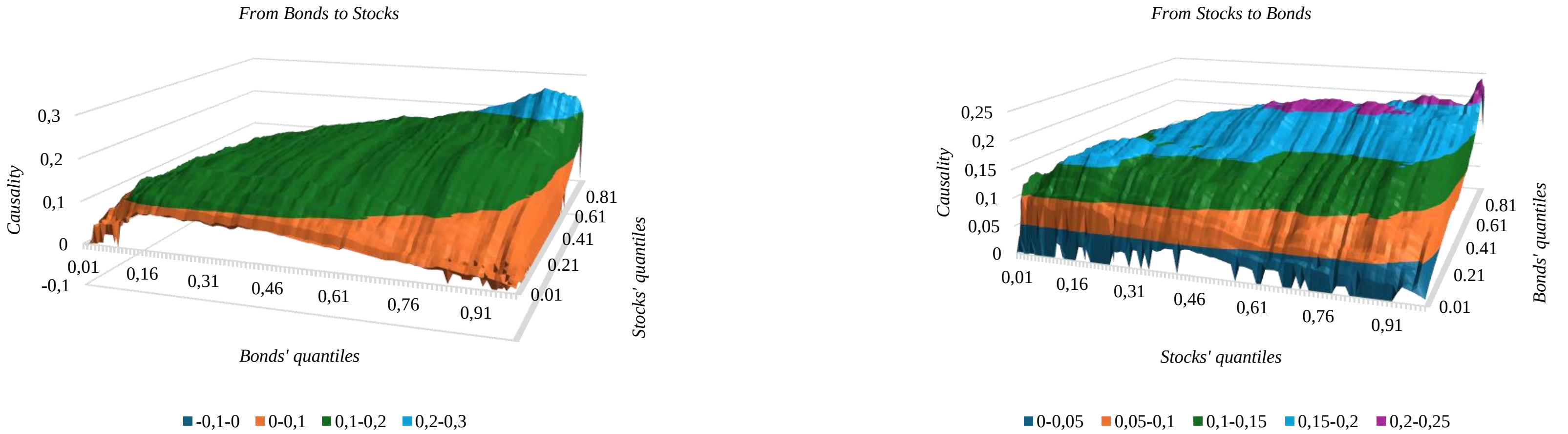
Source: Authors' calculations.

Figure 8. Values of cross-quantilogram indicating directional predictability between stock and bond market volatilities for Germany (9-days lag).



Source: Authors' calculations.

Figure 9. Values of cross-quantilogram indicating directional predictability between stock and bond market volatilities for the U.S. (1-day lag).



Source: Authors' calculations.

4.2. Results on extreme quantiles

In this section, we investigate the dynamic predictability between the financial markets of Germany and the United States, with a particular emphasis on stock and bond markets and their respective volatilities, utilizing three-year rolling windows. Specifically, we analyze directional predictability across various lags (ranging from one to three periods) and different sub-periods, assessing the predominant direction of causality, i.e., from Germany to the United States or vice versa, when analyzing the same asset (bonds or stocks) or within countries, when we intend to analyze the direction of the predictability from stocks to bonds and vice versa. These analyses encompass both rates of return (yield changes) and the volatilities of stock and bond markets.

To account for the time dimension and analyze how causalities evolved, we focus on specific quantiles. We concentrate on extreme quantiles that reflect negative performance in stock markets and negative performance in bond markets (from the perspective of debt servicing costs). We analyze time-varying causality for the quantile of order 0.05 in stock markets and for quantile of order 0.95 in bond markets. When examining causality in volatilities, we focus on the 0.95 quantile, as higher volatility levels are associated with a more difficult stance of financial markets.

Lastly, we emphasize that for all cases, 10,000 bootstrap replications are performed to calculate critical values. Due to the use of bootstrapped critical values, the significance is not always an increasing function of the cross-quantilogram estimate. In some instances, a cross-quantilogram with a lower estimate may exhibit higher significance than one with a higher estimate.

4.2.1. Returns and changes in yields

In Table 2, we present the estimated values of bidirectional predictability between stock returns in the United States and Germany, specifically focusing on the 0.05 quantile, which represents the lowest 5% of stock returns. These estimates are calculated over three-year rolling windows, providing insights into the extreme negative tail dependencies and the dynamic interactions between the two markets.

The period from 1991 to 1993 exhibits a significant positive relationship between U.S. and German stock returns at a two-day lag (0.157***), indicating that extreme negative returns in the U.S. market are followed by similar movements in the German market after two days. This period aligns with the aftermath of the reunification of Germany and the Gulf War, both of which had substantial global economic implications. Additionally, a significant negative causality is observed from German to U.S. stock returns at a three-day lag (-0.053***), suggesting that extreme negative returns in the German market are followed by opposite movements in the U.S. market after three days. This phenomenon can be attributed to the differing economic conditions and recovery trajectories of the two countries during the early 1990s. The Gulf War, which began in August 1990 and ended in February 1991, had indeed a notable impact on stock returns, particularly in the short term. When the conflict broke out, there was a significant initial decline in stock markets due to heightened uncertainty, registering a decline of the S&P 500 by 20%, approximately. The results of the contagion effect between stocks are consistent with the findings of Bonfiglioli and Favero (2005).

The period from 2006 to 2008 is marked by multiple significant positive dependencies, indicative of heightened interconnectedness during the global financial crisis. The bidirectional causality in stock returns between the United States and Germany exhibits significant positive dependencies at various lags, with the most pronounced effect observed at a three-day lag. The global financial crisis, precipitated by the collapse of Lehman Brothers in 2008, resulted in severe market turmoil and heightened volatility. The significant positive dependencies identified during this period underscore the contagion effects and the transmission of financial shocks across international borders, as extensively documented in the literature on financial contagion (Longin and Solnik, 2002; Forbes and Rigobon, 2002; Grammatikos and Vermeulen, 2012; Bekaert et al., 2014).

The period from 2018 to 2020 also exhibits strong bidirectional spillovers, with significant values for both directions, i.e., fromU.S.to DE, DE to US. The causal relationship fromU.S.to Germany is notably strong at a one-day lag (0.236***), suggesting immediate spillover effects from the U.S. to the German market. This period includes significant geopolitical events such as the US-China trade war, notably with the introduction of tariffs and trade barriers (see Afonso et al., 2024b) and Brexit, which created uncertainty and volatility in global markets. The significant positive dependencies during this period align with the findings of previous studies on the impact of geopolitical risks on stock market correlations (Bekaert et al., 2014).

Additionally, we examine the cross-quantilogram relationship of bond market returns between Germany and the United States. The significant relationships identified in the early 1990s, particularly during the 1992-1994 period, where the U.S. to Germany lagged effects at one-day and two-days are positive and significant at the 5% and 1% levels, respectively, can be attributed to the economic adjustments following the reunification of Germany. The reunification imposed substantial fiscal and economic challenges, rendering the German bond market highly sensitive to external shocks, especially from the U.S. These results are consistent with those for stocks.

The late 1990s and early 2000s, characterized by significant cross-quantilogram values, coincide with the dot-com bubble and its subsequent burst. The period 1998-2000, for instance, shows a significant influence of U.S. bond market returns on German returns at the one-day lag (0.085***) and three-days lag (-0.052***). The dot-com bubble was a period of excessive speculation in technology stocks, leading to a market crash that had global repercussions.

The early 2000s also saw the implementation of the Economic and Monetary Union (EMU) and the introduction of the euro, which had a significant effect on bond markets. The convergence of bond yields across Eurozone countries, notably towards the German yields, was influenced by the Stability and Growth Pact and the perceived fiscal discipline among euro area member states. However, the early 2010s brought the European sovereign debt crisis, where fears of fiscal unsustainability in peripheral Eurozone countries led to significant yield spikes and contagion effects (Afonso et al., 2024a). The significant cross-quantilogram values during this period underscore the vulnerability of Germany to the influence of events coming from the U.S., as highlighted by Lakdawala et al. (2021). Furthermore, the results underscore the potential implications of fiscal unsustainability. Higher changes in yields, as captured by the top quantile, often signal concerns about fiscal health and the risk of default. The significant cross-quantilogram values, particularly those indicating positive dependence, suggest that fiscal instability in one country can quickly influence investor perceptions and yield movements in another. This is particularly relevant in the context of the European sovereign debt crisis, where fears of lacking fiscal sustainability led to significant yield spikes and contagion effects across global bond markets.

Table 2. Cross-quantilogram values for 3 years-rolling-windows reflecting relationships between stock market returns in Germany and the United States in quantiles of order 0.05, and relationships between bond market returns in Germany and the United States in quantiles of order 0.95.

Window	*Relationship between stock market returns of order 0.05*						*Relationship between changes in sovereign bond yields of order 0.95*					
	Lag=1		*Lag=2*		*Lag=3*		*Lag=1*		*Lag=2*		*Lag=3*	
	US → DE	*DE → US*	*US → DE*	*DE → US*	*US → DE*	*DE → US*	*US → DE*	*DE → US*	*US → DE*	*DE → US*	*US → DE*	*DE → US*
1991-1993	-0.001	0.078	0.157***	-0.028	0.104**	-0.053***	-0.019	-0.019	0.040	0.010	0.069	0.010
1992-1994	-0.001	0.025	-0.028	-0.027	-0.001	-0.053***	0.095**	0.124	0.153***	0.012	0.066	0.071
1993-1995	-0.001	0.078*	-0.028**	0.027	-0.028***	-0.053***	0.059	0.115	0.115*	0.004	0.087*	0.087**
1994-1996	-0.054***	0.025	-0.001	-0.028***	-0.028***	-0.054***	0.078*	0.130*	0.025	-0.028***	-0.001	-0.001
1995-1997	-0.001	0.078	0.104*	-0.028	0.051	0.000	0.052	0.078*	-0.027***	0.000	0.000	0.000
1996-1998	0.157***	0.157**	0.104*	-0.001	-0.001	0.051	-0.001	0.104	-0.053***	-0.001	0.051*	-0.054***
1997-1999	0.104*	0.104*	0.104**	-0.001	-0.001	-0.028**	0.080	0.107*	0.001	0.000	-0.053***	-0.053***
1998-2000	0.078	0.051	0.080	-0.001	-0.027	-0.028***	0.085	0.167***	0.003	0.003	-0.025	-0.052***
1999-2001	0.078	0.025	0.078	0.025	0.025	-0.054***	0.107**	0.160**	-0.027***	0.027	0.000	0.028
2000-2002	0.078	0.107	0.104	-0.026	0.025	0.032	0.001	0.136*	0.028	0.136*	0.001	0.028
2001-2003	0.104	0.104	0.104	-0.001	0.078	0.027	0.001	0.217***	0.001	0.136***	0.001	0.028
2002-2004	0.157*	0.131**	0.104	0.025	0.051	0.051	-0.025	0.217***	0.001	0.082	0.028	0.001
2003-2005	0.107**	0.052	0.080	0.104*	0.053	0.051	-0.024	0.194**	-0.023	0.004	0.087*	0.062
2004-2006	0.130**	0.051*	0.000	0.051	0.080	0.025	0.115*	-0.023	-0.024	-0.051***	0.059	-0.051***
2005-2007	-0.001	-0.001	0.025	0.025	0.025	0.104**	0.112*	0.112*	0.003	-0.025	0.085***	0.004
2006-2008	0.157*	0.131	0.130*	0.078	0.157**	0.209***	0.136***	0.109**	0.082*	0.082	0.055	0.055
2007-2009	0.131**	0.157***	0.104*	0.052	0.157**	0.130**	0.104*	-0.001	0.025	0.025	0.051	0.025
2008-2010	0.131**	0.131**	0.131**	0.025	0.157***	0.104**	0.083	-0.025	0.055	0.001	0.085**	0.028
2009-2011	-0.001	0.078	0.051	-0.001	0.025	0.025	0.130**	-0.054***	0.078*	-0.027***	-0.001	0.001
2010-2012	0.025	0.104**	0.078	0.051	0.051	0.051	0.080	0.027	0.107**	-0.027***	0.000	-0.027***
2011-2013	0.025	0.078	0.130*	0.078	0.104*	0.104**	0.163***	0.001	0.082*	0.028	-0.053***	-0.053***
2012-2014	0.025	0.052	0.104	0.000	0.051	0.027	0.109*	0.028	0.055	0.028	0.001	-0.026
2013-2015	0.025	0.131**	0.078	0.025	0.025	0.051	0.052	0.000	0.053	0.03	-0.053***	0.003
2014-2016	0.078	0.104	0.025	0.025	-0.001	0.051	0.025	0.025	-0.001	-0.001	-0.054***	0.025
2015-2017	0.078	0.130**	0.025	0.051	-0.054***	0.157***	0.025	0.025	0.000	-0.001	-0.053***	-0.001
2016-2018	0.130*	0.078	0.053	0.051	0.000	0.130**	0.107**	0.025	0.000	-0.028***	-0.027***	0.078*
2017-2019	0.104**	0.104*	-0.001	0.051	-0.001	0.080	-0.027***	0.053	0.080	0.000	0.028	0.055
2018-2020	0.236***	0.183**	0.052	0.157**	0.051	0.104	0.054	0.134**	0.133**	0.107**	0.107	0.133***
2019-2021	0.210***	0.157	0.052	0.157**	0.078	0.078	0.025	0.078	0.131*	0.078	0.051	0.104*
2020-2022	0.157**	0.157**	0.051	0.157**	0.051	0.051	0.107*	0.027	0.053	0.027	0.082	0.055
2021-2023	0.104*	0.051	0.025	0.051	0.051	0.027	0.085	-0.052***	0.085*	0.003	0.030	-0.025
2022-2024Q2	0.106	0.074	0.042	0.042	0.074	0.042	0.012	-0.053***	0.044	-0.020	-0.020	-0.053***

Notes: *,**,*** denote the level of significance of 10%, 5% and 1% levels, respectively. Robust standard deviations are computed but omitted for reasons of parsimony.

We turn our attention now to the cross-asset predictability in both Germany and the U.S.. The analysis of the cross-quantilogram results for the three-year rolling windows in Germany, reflecting the relationship between the lowest 5% stock returns (quantile of order 0.05) and the top 5% changes in bond yields (quantile of order 0.95), presented in Table 3, provides significant insights into the relationship between extreme movements in the stock and bond markets. Within the German market, the bidirectional relationship between bonds and stocks was predominantly positive and significant until the early 21st century, coinciding with the start of the Economic and Monetary Union. This predictable relationship was observed across all lags. Interestingly, the directional relationship from stocks to bonds became more significant after the 21st century, with the sign varying over the years. Specifically, during the sovereign debt crisis, changes in stocks led to opposite changes in bonds. This shift could be attributed to increased market volatility and investor behavior during periods of economic uncertainty, where investors often move their capital between stocks and bonds to manage risk and seek safer investments.

Furthermore, we analyze the cross-relationship between the stock and bond markets for the United States. We highlight the positive bilateral predictability between stock and bond returns in the early 2000s, indicating mutual influences between the two markets. This period coincides with the implementation of the Gramm-Leach-Bliley Act, which significantly impacted financial markets by repealing parts of the Glass-Steagall Act and allowing commercial banks, investment banks, and insurance companies to consolidate. This deregulation contributed to increased market volatility and interdependence between stock and bond markets. Additionally, the 2010s also exhibit periods of positive and significant cross-asset predictability. This period was characterized by uncertainty due to fluctuations in commodity prices, variations in Federal Reserve interest rates, and geopolitical tensions with China. According to Ferrer et al. (2019), during turbulent times, stocks and bonds tend to exhibit positive co-movement.

Table 3. Values of cross-quantilogram for 3 years-rolling-windows reflecting relationship between stock (quantile of order 0.05) and bond market (quantile of order 0.95) returns in Germany and the United States.

Window	*Germany*						*United States*					
	Lag=1		*Lag=2*		*Lag=3*		*Lag=1*		*Lag=2*		*Lag=3*	
	B → S	***S → B***	***B → S***	***S → B***	***B → S***	***S → B***	***B → S***	***S → B***	***B → S***	***S → B***	***B → S***	***S → B***
1991-1993	-0.052	-0.052	0.028**	0.054***	-0.078*	-0.027	-0.098*	0.019	-0.010	-0.040	-0.042	0.019
1992-1994	-0.114	0.028**	0.027	0.001	0.027*	-0.025	0.020	0.020	-0.039	-0.040	-0.039	-0.010
1993-1995	-0.163**	0.026	0.026	-0.028	-0.001	-0.001	-0.028	0.026	-0.057	-0.028	-0.003	-0.109**
1994-1996	-0.183***	0.054***	0.001	0.001	0.028***	0.001	-0.051	0.001	0.001	-0.078*	0.001	-0.078
1995-1997	-0.025	0.028**	0.027	0.053***	0.027*	-0.028	-0.078*	0.001	0.028***	0.028***	-0.025	0.028***
1996-1998	0.027**	0.001	0.028*	0.054***	0.028***	0.001	-0.025	0.027**	0.028**	0.001	0.001	0.028***
1997-1999	0.054***	-0.025	0.028***	0.027	-0.025	0.000	-0.053*	0.000	0.027	-0.027	-0.053	0.000
1998-2000	-0.001	-0.001	0.025	-0.001	-0.057	-0.001	0.000	0.027	0.027**	0.000	-0.053	0.000
1999-2001	-0.025	0.028***	0.001	-0.051	-0.080*	0.001	-0.053*	-0.027	-0.053	0.027	0.000	0.027**
2000-2002	0.053***	0.025	0.027	0.024	0.000	0.050***	0.028***	-0.027	-0.078**	0.027*	-0.027	-0.053
2001-2003	0.054***	-0.025	0.001	-0.051	0.001	0.028***	0.026	-0.001	-0.001	0.026	0.025	-0.055
2002-2004	0.053***	-0.027	0.000	-0.053	0.027	0.027	0.053***	-0.054	0.027	-0.053	0.000	-0.160***
2003-2005	0.023	-0.058	-0.004	-0.06	0.024	0.051***	0.054***	0.028*	0.028***	0.027	-0.078*	-0.001
2004-2006	-0.087	-0.004	0.022	-0.004	-0.062	-0.032	0.028***	0.028**	0.028***	0.028***	0.028***	0.027**
2005-2007	-0.08	-0.027	-0.053	-0.027	-0.027	-0.027	0.026	0.026	-0.055	-0.028	0.053***	-0.085*
2006-2008	-0.055	-0.163**	-0.028	-0.055	-0.001	-0.109**	-0.052	-0.210**	-0.078	-0.157**	0.001	-0.104*
2007-2009	-0.025	-0.104*	-0.025	-0.052	0.001	-0.104	0.001	-0.183***	-0.078	-0.131**	-0.051	-0.051
2008-2010	0.026	-0.054	0.000	-0.053	0.000	-0.107	0.026	-0.160***	-0.053	-0.133***	-0.055	-0.053
2009-2011	-0.051	-0.078*	-0.025	0.028***	-0.051	-0.130***	0.001	-0.078	-0.078*	-0.133**	-0.078	-0.028
2010-2012	-0.053	-0.080*	-0.027	0.027**	-0.053	-0.133***	0.054***	-0.078	0.001	-0.078	0.001	-0.104*
2011-2013	-0.082	-0.055	-0.028	0.026	-0.055	-0.055	0.028***	-0.104	0.028***	-0.078	0.001	-0.104*
2012-2014	-0.001	-0.028	0.026	0.026	0.026	-0.028	0.001	0.028**	0.000	-0.051	-0.027	-0.078
2013-2015	0.027	0.001	-0.028	-0.080**	-0.001	-0.080**	0.001	0.001	0.001	0.000	0.001	0.027*
2014-2016	-0.025	-0.025	0.001	-0.025	-0.051	-0.025	0.028**	0.028**	0.028***	0.028***	0.028***	0.028***
2015-2017	0.001	-0.025	-0.051	-0.053	-0.051	-0.053	0.054***	-0.025	0.001	-0.025	0.028***	0.001
2016-2018	-0.025	-0.027	0.027*	0.027*	-0.027	0.053***	-0.025	0.054***	-0.025	0.028***	0.054***	0.028***
2017-2019	-0.027	0.053***	0.027*	0.027	0.026	0.052***	0.001	0.054***	0.001	0.028***	0.054***	0.001
2018-2020	-0.054	-0.054	0.027	-0.053	-0.027	-0.027	-0.025	-0.104	-0.078	-0.078	-0.025	-0.104*
2019-2021	-0.052	-0.052	0.001	-0.078	-0.025	-0.025	-0.052	-0.104*	-0.052	-0.052	-0.025	-0.104*
2020-2022	-0.052	-0.052	0.001	-0.025	0.000	-0.051	-0.027	-0.107**	-0.053	-0.08	-0.136**	-0.107**
2021-2023	-0.027	-0.053	-0.053	-0.027	-0.080	-0.027	-0.028	-0.082	0.026	-0.055	-0.003	-0.055*
2022-2024Q2	-0.012	-0.044	-0.044	-0.044	-0.109	-0.044	-0.010	-0.074	0.022	-0.042	0.022	-0.042

Notes: *,**,*** denote the level of significance of 10%, 5% and 1% levels, respectively. Robust standard deviations computed but omitted for reasons of parsimony.

4.2.2. Volatilities

Having analyzed the cross-country relationships for stock returns and changes in sovereign bond yields, as well as the causality between stocks and bonds for Germany and the United States, in this subsection we rely on the volatilities of abovementioned relationships.

The analysis of stock returns and changes in sovereign yields is incomplete without a thorough examination of their volatilities. In the realm of portfolio management, volatility analysis is indispensable for constructing diversified portfolios. By evaluating the volatility of various assets, namely stocks and sovereign bonds, investors can optimize the risk-return profile of their portfolios, thereby enhancing their investment strategies. Furthermore, volatility serves as a barometer of market sentiment and investor behavior. Additionally, changes in sovereign yields and their volatility can provide valuable insights into shifts in economic conditions, monetary policy, and investor confidence, making them crucial indicators for macroeconomic analysis and forecasting.

To analyze the causality for all the previously described relationships, we focus on the volatilities over non-overlapping 9-day intervals (t - 4, t, and t + 4) of stock returns and changes in sovereign yields. The results are detailed in Table 4.

During the early 1990s, specifically from 1992 to 1996, the causality from U.S. stock returns volatility to DE stock returns volatility, and vice versa, is consistently negative and statistically significant at the 1% level. However, this effect is also present in the bond markets transmission from Germany to the U.S. and within the domestic market of the U.S. (effect that prolongs until the 2000s). This period coincides with the early 1990s recession, characterized by restrictive monetary policies, the 1990 oil price shock, and the savings and loan crisis in the United States.

As expected, the financial crisis of 2007-2008 had a profound impact on the volatility dynamics between U.S. and DE stock and bond returns as markets move in the same direction, however, in the 2010's the causality is predominantly negative. Align with the findings of Diebold and Yilmaz (2012) and Adrian et al. (2019) regarding the flight-to-safety effect, the results for the 2006-2008, 2007-2009, and 2008-2010 periods show significantly positive causality at the 1% level. These findings support dynamic asset pricing models that suggest the risk premium varies nonlinearly with market volatility. In fact, this period was characterized by severe market turmoil, with the collapse of major financial institutions and unprecedented levels of market volatility. We argue that this synchronized movement is driven by fear and uncertainty, leading to a broad sell-off in riskier markets and a surge in safer ones. After the initial panic subsides, markets start to move in opposite directions as investors reassess the situation and look for opportunities. Different assets respond differently to new information and changing economic conditions. For example, stocks might recover as confidence returns, while bonds might decline if interest rates rise.

In the late 2010's period, the relationship between and within U.S. and DE returns volatility remains significant and positive. The 2018-2020 and 2019-2021 periods show significantly positive causality at the 1% level, suggesting that the interconnectedness between these markets persisted even during the recovery phase. This finding aligns with the increased globalization of financial markets and the continued influence of U.S. market movements on global financial stability.

Table 4. Values of cross-quantilogram for 3 years-rolling-windows reflecting relationship between volatilities in stock markets for quantiles of order 0.95. (Lag=9)

Window	*Stock vs. Stock*		*Bond vs. Bond*		*DE (between markets)*		*US (between markets)*	
	US → DE	***DE → US***	***US → DE***	***DE → US***	***B → S***	***S → B***	***B → S***	***S → B***
1991-1993	0.106	-0.002	0.055	-0.054***	0.160	-0.026	-0.028***	-0.054***
1992-1994	-0.054***	-0.052***	0.262**	0.057	-0.025	0.025	-0.052***	0.077
1993-1995	-0.053***	0.055	0.217**	-0.053***	-0.026	0.028	-0.053***	0.163**
1994-1996	-0.052***	-0.055***	0.051	-0.055***	0.002	0.025	0.104	-0.055***
1995-1997	0.089	0.064	-0.050***	-0.054***	-0.054***	-0.044***	-0.028***	-0.051***
1996-1998	0.262*	0.394***	-0.002	-0.054***	-0.002	0.077	0.025	0.183
1997-1999	0.183	0.183	0.077	-0.054***	0.130	0.077	0.051	0.288**
1998-2000	0.376***	0.183	0.106	-0.028***	0.202	0.183*	0.080	0.266*
1999-2001	0.230**	0.244**	0.104	-0.027***	-0.023	-0.053***	-0.028***	-0.054***
2000-2002	0.183	0.142	0.136	0.104	-0.028***	-0.022	0.077	-0.028***
2001-2003	0.156	0.025	-0.054***	0.008	-0.054***	-0.054***	0.130	0.037
2002-2004	0.446***	0.130	-0.054***	0.104*	-0.028***	0.025	0.157	0.130*
2003-2005	0.441***	0.355**	-0.054***	0.104	0.326**	0.104	-0.05***	-0.054***
2004-2006	-0.002	0.183	-0.055***	0.051	0.288***	0.051	0.077	0.025
2005-2007	-0.053***	0.190	0.284	0.136	0.190*	-0.053***	0.103	0.136
2006-2008	0.526***	0.446***	0.480***	0.183	0.315	0.209	0.240	0.236
2007-2009	0.526***	0.446***	0.315***	0.077	0.288	0.130	0.130	0.183
2008-2010	0.526***	0.446***	0.236**	-0.002	0.288	0.077	0.104	0.130
2009-2011	-0.002	0.051	0.051	-0.021	0.156	0.156	0.130	0.152
2010-2012	0.130	0.394***	0.077	-0.028***	0.104	0.104	0.183*	0.025
2011-2013	0.156	0.499***	0.130	-0.002	0.130	0.104	0.315***	0.025
2012-2014	0.053	-0.028***	-0.049***	-0.054***	-0.054***	0.341***	-0.049***	0.080
2013-2015	0.051	0.307***	-0.050***	-0.052***	-0.025	0.07	-0.022	-0.028***
2014-2016	-0.054***	0.156	-0.054***	-0.054***	0.025	0.025	-0.028***	-0.054***
2015-2017	-0.055***	0.156	-0.055***	-0.027***	0.025	0.025	-0.028***	-0.054***
2016-2018	-0.042***	0.080	-0.05***	-0.050***	0.143	-0.05***	-0.027***	-0.048***
2017-2019	0.156	0.130	-0.028***	-0.050***	0.124	-0.055***	0.025	-0.055***
2018-2020	0.631***	0.526***	0.262	0.183	0.394***	0.367***	0.526***	0.394***
2019-2021	0.631***	0.526***	0.487***	0.209	0.552***	0.595***	0.526***	0.394**
2020-2022	0.420**	0.499***	0.051	0.025	0.025	-0.054***	0.526***	0.341**
2021-2023	0.163	0.109	0.109	-0.026	-0.026	0.136	0.298**	-0.053***
2022-2024Q2	0.201	0.105	0.105	-0.023	-0.055***	0.105	0.265**	-0.055***

Notes: *,**,*** denote the level of significance of 10%, 5% and 1% levels, respectively. Robust standard deviations computed but omitted for reasons of parsimony.

4.3. The impact of Financial Stress Index and Monetary Policy Shocks

The calculations presented in the preceding sections were designed to elucidate the dependency of causality between stock market returns, changes in yields, and volatilities on the quantiles of their respective distributions (Figures 1-8). Furthermore, these calculations highlighted the temporal fluctuations of the causality measure within three-year overlapping windows. In this section, our objective is to discern the influence of various categories on these time-varying causality measures.

The causality measures calculated in the previous subsection are presented within overlapping windows. However, to obtain a time series of independent observations, it is necessary to calculate these values within non-overlapping windows. Consequently, we generated time series for 48 variants, with causality measures computed in non-overlapping windows.

Subsequently, we employed standard unit root tests, specifically the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979, 1981) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992), to determine the order of integration of the variables reflecting causality. Table 5 presents information on causalities that are integrated of order 1, as both tests confirmed the non-stationarity of levels and the stationarity of first differences. Additionally, it includes causalities that may be integrated of order 1, where one test indicated non-stationarity at the level and stationarity at the first difference, while the other test indicated stationarity at the level.[8]

Table 5. Measures of causality, which turned out to be integrated of order 1 or may be integrated of order 1

Causality	*Lags*	*Order of integration*
From the U.S. stock market to the DE stock market	2	I(0) or I(1)
From the U.S. bond market to the DE bond market	2	I(0) or I(1)
From DE bond market to the U.S. bond market	1	I(1)
From volatility of the DE bond market to volatility of the U.S. bond market	9	I(0) or I(1)

In addition to understanding the order of integration of causality measures, it is essential to determine the order of integration for the variables used as determinants of causality. Table 6 presents the results of tests conducted to ascertain the order of integration for these factors.

The results presented in Table 6 indicate that certain time series of exchange rates may be generated by stochastic processes integrated of order 1. The primary balance for the United States is identified as a trend-stationary variable. For variables identified as I(1), we treat them accordingly. In the case of non-stationary causality measures, we seek to identify long-run

[8] For causalities not listed in Table 5, the tests indicated stationarity.

relationships between causality and variables reflecting exchange rates. Subsequently, we estimate the parameters of an error correction model to explain changes in causality using stationary variables. When causality measures are stationary, we estimate the parameters of a standard linear regression model with stationary regressors, utilizing the first differences of variables associated with exchange rates.

Table 6. Testing order of integration of variables considered as determinants of causalities

	Level		*First difference*		**Decision**
	ADF statistic	*KPSS statistic*	*ADF statistic*	*KPSS statistic*	
FSI	-2.65 (n,1)	0.08	-	-	I(0)
MPS_s^{ECB}	-4.60 (d,1)	0.09	-	-	I(0)
MPS_s^{Fed}	-4.94 (n,1)	0.08	-	-	I(0)
$CAPB_s^{DE}$	-4.20	0.22	-	-	I(0)
$CAPB_s^{US}$	-6.38 (t,1)	0.11	-	-	I(0), after detrending
$REER_s^{DE}$	-2.97 (d,1)	0.09	-3.90 (n,0)	-	I(0) or I(1)
$REER_s^{US}$	0.92 (n,1)	0.43	-2.37 (n,0)	-	I(0) or I(1)
$EXRATE_s^{USD/EUR}$	-2.33 (d,1)	0.10	-2.96 (n,0)	-	I(0) or I(1)

Notes: t,d,n indicates that a model with trend, with drift and without drift was used in regression of the ADF test.

Table 7. Econometric models explaining time-varying causality

Model	***Markets (direction)***	***Countries (direction)***	***Lag***	***Short-run (S) or long-run (L) equation***
1	$S \rightarrow S$	$US \rightarrow DE$	1	S
2	$B \rightarrow B$	$US \rightarrow DE$	1	S
3	$B \rightarrow B$	$US \rightarrow DE$	3	S
4	$B \rightarrow B$	$DE \rightarrow US$	1	S & L
5	$B \rightarrow B$	$DE \rightarrow US$	2	S
6	$B \rightarrow S$	DE	1	S
7	$S \rightarrow B$	DE	1	S
8	$S \rightarrow B$	DE	3	S
9	$B \rightarrow S$	US	1	S
10	$S \rightarrow B$	US	3	S
11	$B \rightarrow S$	US	1	S
12	$B \rightarrow S$	US	3	S
13	$S \rightarrow S$ (Vol.)	$US \rightarrow DE$	9	S
14	$B \rightarrow S$ (Vol.)	DE	9	S

Notes: *S*, *B*, and Vol. stand for Stocks, Bonds and volatility, respectively.

Table 8. Results of the estimation of parameters of regression models explaining causalities

Model	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**	**M10**	**M11**	**M12**	**M13**	**M14**
Markets	$S \rightarrow S$	$B \rightarrow B$	$B \rightarrow B$	$B \rightarrow B$	$B \rightarrow B$	$B \rightarrow S$	$S \rightarrow B$	$S \rightarrow B$	$B \rightarrow S$	$S \rightarrow B$	$B \rightarrow S$	$B \rightarrow S$	$S \rightarrow S$ (Vol.)	$B \rightarrow S$ (Vol.)
Direction (country)	*US → DE*	*US → DE*	*US → DE*	*DE → US*	*DE → US*	*DE*	*DE*	*DE*	*US*	*US*	*US*	*US*	*US → DE*	*DE*
Lag	1	1	3	1	2	1	1	3	1	3	1	3	9	9
const	-	-	-	-0.311 (0.216)	-	-	-	-	-	-	-	-	-	-
$EXRATE_s^{USD/EUR}$	-	-	-	0.457* (0.252)	-	-	-	-	-	-	-	-	-	-
CIDF statistic	-	-	-	-5.350***	-	-	-	-	-	-	-	-	-	-
ECT	-	-	-	-1.263*** (0.213)	-	-	-	-	-	-	-			
const	0.072*** (0.019)	0.056*** (0.011)	0.017 (0.012)	-	-	-0.048*** (0.014)	-0.008 (0.011)	-0.019 (0.013)	0.010 (0.014)	-0.006 (0.011)	0.002 (0.015)	-0.019 (0.011)	0.055* (0.032)	0.072* (0.039)
FSI	-	-	-	-	-	-	-0.019** (0.007)	-0.019** (0.009)	-	-	-0.021** (0.010)	-	0.089*** (0.022)	0.053* (0.027)
MPS_s^{ECB}	0.232* (0.111)	-	-	-	0.139* (0.074)	-	-	-	-	-0.138* (0.067)	-	-	-	-
MPS_s^{Fed}	-	-	-	-	-	-0.094** (0.041)	-	-	0.103** (0.040)	-	-	-	-	-
$CAPB_s^{DE}$	-0.032* (0.018)	-	-	-	-	-	-	-	-	0.026** (0.011)	-	-	-	-
$CAPB_s^{US}$	-	-0.019** (0.009)	-	-	0.021* (0.011)	-	-	0.019** (0.009)	-	-	-	-	-	-
$\Delta\ EXRATE_s^{USD/EUR}$	-	-	-0.322* (0.171)	-	-	-	0.284** (0.135)	-	-	-	-	0.343** (0.150)	-	-
R-squared	0.311	0.172	0.151	0.626	0.337	0.201	0.266	0.326	0.238	0.534	0.178	0.206	0.442	0.156

Notes: *const* are the constant, $REER_s^{DE}$ and $REER_s^{US}$ are the Real Effective Exchange rate of Germany and the US, respectively, $EXRATE_s^{USD/EUR}$ is the bilateral exchange rate between USD and EUR. *CIDF statistic* is used for testing whether cointegration occurs and, *ECT* is the error correction term. *FSI* is the Financial Stress indicator, MPS_s^{ECB} and MPS_s^{Fed} are the Monetary policy shocks of Germany and the US, respectively, $CAPB_s^{DE}$ and $CAPB_s^{US}$ are the Primary balance of Germany and the US, respectively, $\Delta EXRATE_s^{USD/EUR}$ is the change in the bilateral exchange rate between USD and EUR. *,**,*** denote the level of significance of 10%, 5% and 1% levels, respectively. In parentheses are the standard deviation.

With the purpose of explaining causality, Table 7 summarizes the fourteen models we utilize to analyze the impact of financial stress index, monetary policy shocks, fiscal primary balance and exchange rate on cross-quantilogram predictability, while Table 8 reports the estimation parameters of the regression models.

Examining Table 8, the cointegrating relation results indicate that during periods of a stronger U.S. dollar-euro exchange rate, $EXRATE_s^{USD/EUR}$, changes in the 10-yearU.S.sovereign bond yields to increases of the 10-year sovereign bond yields in Germany was more intensive (Model 4 of the Long-run equation). In other words, the reactions of theU.S.10-year bond yields to changes in 10-year German bond yields at the 0.95 quantile of both variables are stronger when the euro is weaker. This finding suggests an inverted uncovered interest rate parity consistent with Czudaj and Prüser (2015) who also identified a bidirectional relationship between long-term interest rates and exchange rate for Germany and the United States. However, prior empirical studies (Czudaj and Prüser, 2015) have shown that U.S. economic variables exert a stronger influence on Germany than vice versa.

In the short term, exchange rate fluctuations also play a moderating role. Models 3 and 7 show that as the euro appreciates against the U.S. dollar, causality from the U.S. bond market to the German bond market increases. Conversely, when the euro weakens, causality from the German stock market to the German bond market intensifies. This suggests that exchange rate dynamics influence the interplay between Germany's stock and bond markets.

Further, the European Central Bank monetary policy shocks (MPS_s^{ECB}) emerge as critical drivers of causality between German and U.S. markets (Models 1, 5, and 10). For instance, the negative reaction of Germany rates of return to a significant decline of the S&P 500 is more pronounced during periods of positive monetary policy shocks (Models 1). This result aligns with the results present in Table 2 during the 2006-2008 period and with Kazi et al. (2013), who noted that the impact of monetary policy shocks varies over time and international propagation of shocks is more intensive during turbulent periods. Monetary policy shocks of the European Central Bank also report a significant impact on causality between the German bond market and the U.S. bond market (Model 5). Indicating that raising the reference rate resulted in significant increase of 10-year sovereign bond yields in Germany, which later transmitted to the U.S. bond market. We also observe that the U.S. treasury bond market adjusted to the tightening of monetary policy in the euro zone in Model 10.

In contrast, the U.S. Federal Reserve monetary policy shocks (MPS_s^{Fed}) affect causality within the domestic market. Specifically, Model 9 shows that a lower-than-expected rising Fed reference rate reduces causality from the U.S. bond market to the U.S. stock market (positive estimate coefficient of 0.103). This finding aligns with Miranda-Agrippino and Ricco (2021), who demonstrated that a monetary tightening in the U.S. is contractionary, with deterioration of domestic demand, labour, prices of assets and agents' expectations.

The fiscal primary balance also significantly impacts cross-market dynamics. In Germany, a higher primary balance strengthens the resilience of the German stock market to negative returns in the U.S. stock market (Model 1). This result, derived from data spanning 1990-2024, contrasts with earlier studies (e.g. Afonso and Sousa, 2011), which found that fiscal shocks had a minimal impact on Germany's asset markets prior to 2008. However, the role of fiscal policy has grown substantially since the Global Financial Crisis and subsequent crises. In the U.S., fiscal policy behaves differently. Model 5 reveals that a higher primary balance does not improve the resilience of the U.S. bond market to negative shocks from Germany, a counterintuitive result.

The financial stress indicator also demonstrates consistent significance across Models 7, 8, 11 and 13-14. During periods of heightened financial stress, causality from the German stock market to the German bond market decreases (Models 7 and 8), suggesting that German sovereign bonds act as a safe haven. This finding aligns with Dajcman (2012), who observed that during periods of market volatility, the correlation between stock market returns and sovereign bond yield dynamics differed between Germany and countries affected by the sovereign debt crisis. Further, the author showed that in Germany this correlation was predominantly positive, whereas in the affected countries, it was largely negative.

Lastly, for the US, financial stress impacts causality between its bond and stock markets in more complex ways. Model 11 reveals that using a one-day lag, impact of financial stress on causality turned out to be negative. Moreover, in periods of higher financial stress, causality in volatility intensifies, as expected (Models 13 and 14).

4.3. Robustness Analysis

To have a clear view of the predictability relationship between stocks and bonds in Germany and the United States, in this subsection we explore the causality interdependence between these two markets considering quantile of order 0.95 for stocks and 0.05 for bonds (Tables A1 and A2 in the Appendix). Further, we analyze the change in volatility in stock and bonds for quantile of order 0.05, in Table A3 of the Appendix.

During the 1990s (Table A1), the aftermath of the Gulf War and German reunification led to negative causality from U.S. to German highest quantiles in stock markets. However, Germany's economic recovery positively influenced the U.S. stocks. Similar trends persisted throughout the 1990s, influenced by events such as the Maastricht Treaty and European integration, which created uncertainties and adjustments in German markets while highlighting the growing influence of U.S. financial dynamics on Germany.

During the 21st century, mutual positive causality emerged in the highest quantiles of stocks, particularly after the dot-com bubble and the September 11 attacks, underscoring the high interdependence of the markets in times of crisis. This pattern continued during the 2007–2009 global financial crisis, where shocks originating in the U.S. had profound global effects. The positive causality in both directions highlighted the interconnectedness of financial systems and the role of coordinated monetary and fiscal policy responses. Similar trends were observed during subsequent crises, including the European sovereign debt crisis from 2011 to 2013, the Brexit referendum, and the U.S. presidential election from 2016 to 2018, where global uncertainties heightened market interdependencies. The COVID-19 pandemic further reinforced the bilateral causality between markets, reflecting their global nature and the synchronized policy responses to mitigate volatility and risks.

Parallel analyses of bond yields revealed similar interdependencies. Before the 21st century, the majority of the relationship between the two markets is negative. For instance, changes in the lowest quantiles of bond yields in the U.S. typically affect in a opposite direction changes in German bonds. During crises, such as the 2008 financial crises U.S. monetary policy and macroeconomic stability often influenced positively German bond markets. Conversely, Germany's robust economic performance in certain periods (for example, the Covid 19 period) also impacted the U.S. bond yields, illustrating a two-way connection, which confirm the causal relationship observed in Table 2. Additionally, in Germany and in the U.S. (Table A2 in the Appendix), there is a clear increase in the predictability of cross assets after the 2008 financial crisis.

The volatility analysis (Table A3 in the Appendix) further showed significant mutual influences, especially for the lowest volatilities of stocks. When volatility decreases in one stock market, it signals stability, encouraging similar behavior in connected markets. For the bond market, further corroborates this financial integration, as movements from the U.S. and from Germany display similar signals and behavior throughout the year. Further, in Germany during the global financial crisis and in the COVID-19 pandemic a reciprocal transmission of shocks and the critical role of coordinated policy measures in stabilizing financial systems. This pattern is also clear in the U.S. for the 2000s and the late 2010s.

5. Concluding Remarks and Policy Implications

In this study, we address a significant gap in the literature by utilizing a novel methodological approach to examine the stock-sovereign bond relationships in the U.S. and Germany over the period of 1990-2024. Through the application of the cross-quantilogram method, the analysis provides a nuanced understanding of these relationships, particularly during periods of financial market stress. By offering a comprehensive examination of both within country and cross-country dynamics, this research aims to advance our understanding of financial market behavior and provides meaningful insights to both academic research and practical policymaking.

Specifically, we analyze directional predictability across various lags (ranging from one to three periods) and different sub-periods, assessing the predominant direction of causality, i.e., from Germany to the United States or vice versa. When analyzing the same asset (sovereign bonds or stocks) or within countries, we examined the direction of the predictability from stocks to bonds and vice versa. These analyses encompass both rates of return (yield changes) and the volatilities of stock and bond markets. To the best of our knowledge, this is the first study to apply this methodology to the problem of causality in variance. Lastly, we examine the impact of financial stress, monetary policy shocks, fiscal stance and exchange rates on causality in extreme quantiles of distribution of rates of return, changes in sovereign bond yields, stock market volatilities and bond volatilities. This analysis applies the error correction model for non-stationary causalities and standard linear regression model for stationary causalities.

Firstly, our analysis reveals significant patterns in the cross-relationships between stock and bond markets in the U.S. and Germany. In the early 1990s, extreme negative stock returns in the U.S. were followed by similar movements in Germany, while negative returns in Germany led to opposite movements in the U.S. This can be attributed to differing economic conditions and recovery trajectories. The period from 2006 to 2008 showed heightened interconnectedness during the global financial crisis, and from 2018 to 2020, strong bidirectional spillovers were observed, influenced by geopolitical events like the US-China trade war and Brexit.

In the bond markets, the European sovereign debt crisis highlighted significant yield spikes and contagion effects, emphasizing the mutual transmission of financial shocks between the U.S. and Germany. Within Germany, the bidirectional relationship between bonds and stocks was positive and significant until the early 21st century, becoming more variable post-2000 with the introduction of the Euro. Particularly, during the sovereign debt crisis, heightened market volatility and risk-averse investor behavior caused stocks and bonds to move in opposite directions as investors shifted capital to manage risk. Similarly, in the U.S., the early 2000s showed positive bilateral predictability between stock and bond returns, with the 2010s marked by significant cross-asset predictability. In both the U.S. and in Germany markets, we conclude that during financial crises periods, volatility events in one market led to a synchronized movement in the other.

Secondly, we devote our analysis to the determinants of the causal bilateral predictability between the U.S. and Germany. We conclude that in the short term, exchange rate fluctuations play a moderating role. When the euro appreciates against the U.S. dollar, causality from the U.S. bond market to the German bond market increases. Conversely, when the euro weakens, causality from the German stock market to the German bond market intensifies, indicating that exchange rate dynamics influence the interplay between Germany's stock and bond markets.

We observe a negative reaction of Germany returns to a significant decline of the S&P 500, which was more pronounced during periods of positive monetary policy shocks. European Central Bank Monetary policy shocks significantly impact the causality between German bond market and U.S. bond market. Thus, raising the reference rate leads to increased sovereign bond yields in Germany, which then transmitted to the U.S. bond market. The U.S. bond market also adjusts to tightening monetary policy in the euro zone. In addition, a lower-than-expected rising Fed reference rate reduces causality from the U.S. bond market to the U.S- stock market.

Fiscal primary balance significantly impacts cross-market dynamics. In Germany, a higher primary balance strengthens the resilience of the German stock market to negative returns in the U.S. stock market. In the U.S., however, a higher primary balance does not improve the resilience of the U.S. bond market to negative shocks from Germany.

Lastly, we consistently find statistical significance for the financial stress indicator. Hence, during periods of heightened financial stress, causality from the German stock market to the German bond market decreases, suggesting that German sovereign bonds act as a safe haven in a flight-to-safety context. In the U.S., financial stress impacts causality between its bond and stock markets negatively for a one-day lag. Moreover, during periods of higher financial stress, causality in volatility intensifies, as expected.

Our findings highlight the importance of policymakers and investors to understand the dynamic interactions between the U.S, and Germany to anticipate and mitigate the impact of global financial shocks. Therefore, our study reveals a complex network of causality influenced by historical events, macroeconomics variables, and policy coordination, demonstrating the profound interconnection between these two major markets. Future research could extend this analysis to other markets.

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Appendix

Table A1. Values of Cross-quantilogram values for 3 years-rolling-windows reflecting relationships between stock market returns in Germany and the United States in quantiles of order 0.95, and relationships between changes in sovereign bond yields in Germany and the United States in quantiles of order 0.05.

Window	*Relationship between stock market returns of order 0.95*						*Relationship between changes in sovereign bond yields of order 0.05*					
	Lag=1		*Lag=2*		*Lag=3*		*Lag=1*		*Lag=2*		*Lag=3*	
	US → DE	*DE → US*	*US → DE*	*DE → US*	*US → DE*	*DE → US*	*US → DE*	*DE → US*	*US → DE*	*DE → US*	*US → DE*	*DE → US*
1991-1993	-0.054***	0.183***	0.025	0.025	-0.001	0.051	-0.007	0.018	-0.032**	-0.007	-0.032**	-0.007
1992-1994	-0.028***	0.053	-0.028***	0.027	-0.028***	-0.027***	0.052	0.104*	0.051	-0.001	0.025	-0.001
1993-1995	0.001	0.028	0.028	0.028	0.001	0.001	-0.001	0.157***	0.025	0.000	-0.028*	0.027
1994-1996	-0.028***	0.025	-0.028***	-0.001	-0.001	-0.028***	-0.003	0.076	0.023	-0.029***	-0.055***	-0.003
1995-1997	0.000	0.160**	-0.026	-0.026	0.055	-0.026	-0.001	-0.001	0.025	-0.001	0.027	-0.028
1996-1998	0.052	0.078	-0.001	0.052	0.078	0.051	-0.027	-0.001	-0.001	0.052	0.051	-0.028
1997-1999	-0.001	0.052	-0.054***	-0.001	-0.001	0.051	-0.029	0.050	-0.003	0.076	0.049	-0.029**
1998-2000	0.000	0.025	-0.053***	-0.001	0.080	0.025	-0.054***	0.078	0.025	0.051	-0.027	0.000
1999-2001	-0.001	0.025	-0.028***	-0.001	0.000	-0.027***	-0.028	0.078	-0.053***	-0.001	-0.027	-0.001
2000-2002	0.025	0.025	0.025	-0.001	0.025	0.025	0.016	0.090	-0.033***	-0.009	-0.058***	-0.008
2001-2003	0.052	0.052	0.104	0.051	0.078	0.025	0.025	-0.001	-0.027	-0.054***	-0.053***	-0.027
2002-2004	0.078	0.131**	0.157**	0.104*	0.078	0.051	0.022	0.048	-0.029**	-0.004	-0.055***	-0.055***
2003-2005	0.025	0.131***	0.107	0.051	0.082	0.053	-0.008	0.041	-0.009	-0.033***	-0.033***	-0.058***
2004-2006	-0.001	-0.001	-0.054***	0.000	0.104*	0.000	-0.001	-0.001	-0.028	-0.054***	-0.028	-0.001
2005-2007	0.055	0.001	-0.026	-0.053***	0.082	-0.026	0.022	-0.031***	0.023	-0.005	0.049	-0.005
2006-2008	0.160**	0.107***	0.027	0.001	0.053	0.112*	0.102*	0.050	0.154***	-0.003	0.076	0.076*
2007-2009	0.157***	0.052	0.025	0.025	0.104*	0.130**	0.128*	0.024	0.102*	-0.055***	0.050	-0.001
2008-2010	0.157***	0.052	0.025	0.025	0.104*	0.078	0.128**	-0.002	0.102*	-0.029*	0.050	-0.001
2009-2011	0.051	0.080	0.130**	0.053	0.053	0.082*	0.167*	0.017	0.067	-0.007	-0.032***	-0.008
2010-2012	0.051	0.130**	0.078	0.025	0.051	0.051	0.128*	0.024	0.102**	0.049	-0.003	-0.003
2011-2013	0.051	0.157***	0.051	0.051	0.051	0.051	0.128*	0.050	0.049	0.049	-0.003	0.049
2012-2014	0.025	0.052	0.000	0.025	0.080	0.000	-0.029	-0.002	0.024	0.024	-0.003	-0.003
2013-2015	0.025	0.131**	-0.028***	0.000	-0.001	0.001	0.022	-0.055***	0.022	-0.004	0.022	-0.030***
2014-2016	-0.028***	0.157**	-0.001	0.051	-0.054***	0.051	-0.005	-0.030***	0.022	-0.005	-0.004	-0.031***
2015-2017	-0.028***	0.130*	-0.001	0.051	-0.028***	0.104*	-0.005	-0.030***	-0.005	0.020	-0.031***	0.022
2016-2018	0.025	0.078*	0.160**	0.078*	-0.026	0.187***	-0.007	-0.007	-0.006	0.044	0.019	0.071
2017-2019	0.078	0.025	0.107**	-0.028***	0.000	0.078	-0.003	0.076	0.023	0.049	0.023	0.023
2018-2020	0.104	0.104**	0.052	0.183***	0.078	0.157*	0.025	0.104	0.025	0.078*	-0.028	0.025
2019-2021	0.104	0.104	0.080*	0.183***	0.080	0.183**	0.102*	0.154***	0.024	0.050	-0.001	0.050
2020-2022	0.104	0.078**	0.051	0.236***	0.025	0.104	0.102*	0.154**	0.154***	0.076	0.130***	0.078*
2021-2023	0.082	0.001	0.057	0.055	-0.052***	-0.053***	0.073	0.125*	0.128**	0.125**	0.075	-0.004
2022-2024Q2	0.042	-0.022	0.042	0.074	-0.054***	-0.054***	0.042	0.138**	0.106	0.106	0.074	0.010

Notes: *,**,*** denote the level of significance of 10%, 5% and 1% levels, respectively. Robust standard deviations computed but omitted for reasons of parsimony.

Table A2. Values of cross-quantilogram for 3 years-rolling-windows reflecting relationship between stock (quantile of order 0.95) and bond market (quantile of order 0.05) returns in Germany and in the United States.

Window	*Germany*						*United States*					
	Lag=1		*Lag=2*		*Lag=3*		*Lag=1*		*Lag=2*		*Lag=3*	
	B → S	*S → B*	*B → S*	*S → B*	*B → S*	*S → B*	*B → S*	*S → B*	*B → S*	*S → B*	*B → S*	*S → B*
1991-1993	-0.078*	-0.025	-0.052	0.028	-0.025	-0.025	-0.043	0.007	-0.142***	0.007	-0.042	0.007
1992-1994	-0.078	0.001	-0.025	-0.025	0.001	0.028*	-0.107*	0.001	-0.053	0.001	-0.053	0.001
1993-1995	-0.133**	0.053***	0.000	-0.027	-0.027	0.000	-0.027	0.027	-0.027	-0.028	0.000	0.026
1994-1996	-0.128*	0.029***	0.003	-0.049	-0.049	-0.023	-0.104	0.001	0.028**	-0.078	0.028***	0.054***
1995-1997	0.001	0.000	0.054***	0.053***	0.028**	0.052***	-0.025	-0.053	-0.025	-0.001	0.001	-0.028
1996-1998	0.027	-0.104*	-0.052	0.001	-0.025	0.001	-0.052	-0.025	-0.052	-0.052	-0.025	-0.130**
1997-1999	0.001	-0.052	-0.051	-0.025	0.001	0.001	-0.024	-0.050	-0.102*	-0.024	-0.023	-0.076
1998-2000	-0.027	-0.025	-0.053	-0.025	-0.027	0.000	0.001	-0.051	-0.025	-0.025	0.001	-0.027
1999-2001	0.001	0.054***	0.054***	0.028**	-0.027	-0.053	-0.025	-0.025	-0.027	0.028	0.027	0.028
2000-2002	0.003	0.055***	-0.023	-0.023	-0.025	-0.075**	-0.042	-0.018	0.007	0.007	0.008	-0.042
2001-2003	0.028	0.001	-0.051	0.027	-0.025	-0.080**	-0.052	0.001	0.028	0.001	0.028*	-0.053
2002-2004	0.001	0.001	-0.052	-0.052	0.001	-0.078	-0.022	0.029***	0.029***	-0.022	0.030***	-0.022
2003-2005	0.029**	-0.050	-0.078	-0.050	-0.080**	-0.049	0.007	0.032***	-0.018	-0.067*	0.006	-0.017
2004-2006	0.001	0.001	0.028	0.000	-0.025	-0.027	0.001	-0.025	-0.025	-0.025	0.028*	0.028*
2005-2007	-0.027	0.027	-0.027	0.000	-0.027	-0.027	0.003	-0.073	-0.104*	-0.022	-0.025	-0.022
2006-2008	-0.102**	-0.052	0.029***	0.027	-0.049	-0.055	-0.104	-0.053	-0.210***	-0.160**	-0.104	-0.107**
2007-2009	-0.024	0.002	0.029**	0.029***	-0.050	-0.024	-0.052	-0.052	-0.131*	-0.104	-0.130	-0.080*
2008-2010	0.002	0.028***	0.029***	0.002	-0.050	0.003	-0.052	-0.052	-0.131*	-0.131**	-0.130	-0.053
2009-2011	0.006	-0.044	-0.069	0.006	-0.071	0.006	0.028**	-0.024	-0.051	-0.102**	-0.053	0.029***
2010-2012	-0.102**	-0.128**	-0.076	-0.049	-0.075	-0.049	-0.025	-0.025	-0.104**	-0.130*	-0.078	0.054***
2011-2013	-0.104*	-0.130*	-0.183***	-0.025	-0.130**	-0.078	-0.050	-0.076**	-0.076	-0.076	-0.075	0.055***
2012-2014	-0.078	-0.052	-0.027	-0.051	0.027	-0.078*	0.055***	0.029**	-0.024	0.029***	-0.104**	0.003
2013-2015	0.004	-0.022	-0.099**	0.004	0.004	0.030***	0.028*	0.054***	-0.107**	0.001	-0.136**	-0.025
2014-2016	-0.020	0.030***	-0.071*	0.03***	-0.020	0.030***	0.028*	0.054***	-0.025	-0.025	-0.130**	-0.025
2015-2017	-0.048	-0.022	-0.022	0.03***	-0.022	0.030***	0.029***	0.003	-0.023	-0.049	-0.128**	-0.078**
2016-2018	-0.069*	-0.019	0.031***	-0.020	0.005	-0.022	-0.024	-0.102**	0.055***	-0.107*	-0.023	-0.082*
2017-2019	-0.024	-0.05	0.001	-0.023	0.028*	0.055***	0.001	0.001	0.001	-0.025	-0.051	-0.025
2018-2020	-0.052	-0.025	-0.025	0.001	0.028	0.001	-0.104	-0.078	-0.104*	-0.025	-0.130**	-0.078
2019-2021	-0.025	-0.025	-0.027	0.028	0.027	0.000	-0.154***	-0.076	-0.076	0.002	-0.128**	-0.050
2020-2022	-0.104*	0.028	-0.051	0.001	0.001	-0.027	-0.050	-0.076	-0.050	-0.024	-0.154***	-0.104*
2021-2023	-0.080	0.053***	-0.001	0.000	0.026	-0.053	-0.023	-0.023	0.001	0.003	-0.104*	-0.023
2022-2024Q2	-0.106*	0.054***	0.022	-0.010	0.022	-0.074	-0.010	-0.042	0.022	-0.010	-0.074	-0.010

Notes: *,**,*** denote the level of significance of 10%, 5% and 1% levels, respectively. Robust standard deviations computed but omitted for reasons of parsimony.

Table A3. Values of cross-quantilogram for 3 years-rolling-windows reflecting relationship between volatilities in stock markets for quantiles of order 0.05. (Lag=9)

Window	*Stock vs. Stock*		*Bond vs. Bond*		*DE (between markets)*		*US (between markets)*	
	US → DE	***DE → US***	***US → DE***	***DE → US***	***B → S***	***S → B***	***B → S***	***S → B***
1991-1993	-0.054***	-0.028***	-0.054***	-0.028*	0.130	-0.054***	-0.028	-0.054***
1992-1994	-0.052***	-0.002	-0.026	0.077	0.130	-0.054***	0.001	-0.052***
1993-1995	-0.028**	-0.002	-0.052***	-0.028**	-0.055***	-0.053***	-0.027	-0.002
1994-1996	-0.055***	-0.025	-0.024	0.156*	-0.028***	-0.021	-0.028***	0.051
1995-1997	-0.054***	-0.022	-0.050***	0.066	-0.025	-0.028***	-0.045***	0.059
1996-1998	-0.028***	0.194*	0.112	0.051	-0.054***	-0.025	-0.052***	-0.028***
1997-1999	-0.053***	-0.054***	0.139	0.051	0.000	-0.054***	-0.025	0.026
1998-2000	-0.055***	0.051	0.104	0.025	0.104	-0.055***	-0.028***	0.025
1999-2001	-0.051***	0.156	-0.028***	0.025	0.104	-0.055***	-0.002	0.033
2000-2002	-0.055***	0.209**	-0.002	0.053	0.106	-0.055***	-0.002	0.025
2001-2003	0.010	0.149	0.025	-0.053***	-0.053***	0.064	-0.054***	-0.019
2002-2004	0.005	0.101	0.032	-0.054***	0.104	0.220*	0.059	-0.051***
2003-2005	0.087	-0.050***	0.007	-0.054***	-0.028**	0.124	0.035	0.059
2004-2006	0.035	-0.025	-0.026	-0.002	-0.028***	0.057	0.001	0.263**
2005-2007	0.025	0.051	0.059	0.130*	-0.028***	-0.024	0.025	0.156
2006-2008	0.000	0.077	0.084	0.213**	0.026	0.030	0.051	0.080
2007-2009	0.145	0.232**	0.082	0.186	0.194*	0.061	0.249*	0.057
2008-2010	0.273*	0.220*	0.130*	0.026	-0.054***	0.130*	-0.002	0.010
2009-2011	0.209*	0.209**	0.130*	0.025	-0.028***	0.130**	-0.002	0.077
2010-2012	0.221**	0.130	0.100	-0.026	0.061*	-0.009	-0.053***	-0.028***
2011-2013	0.149	0.025	0.053	0.004	0.092	-0.055***	-0.054***	0.031
2012-2014	0.000	-0.028**	0.025	0.000	-0.028**	-0.028**	0.051	0.001
2013-2015	0.030	-0.002	0.077	0.023	-0.026	-0.029***	0.053	-0.002
2014-2016	0.051	-0.021	0.055	-0.025	-0.054***	-0.023	0.059	0.001
2015-2017	0.030	0.026	0.053	-0.054***	-0.027	0.000	-0.027	0.084
2016-2018	0.025	0.025	-0.055***	-0.055***	-0.055***	-0.002	-0.028**	0.025
2017-2019	0.030	-0.05***	-0.053***	-0.055***	0.002	-0.002	-0.019	-0.002
2018-2020	0.262*	0.077	-0.024	-0.054***	0.051	-0.054***	-0.024	0.183**
2019-2021	0.104	0.025	-0.028**	-0.028**	0.077	-0.054***	-0.054***	0.051
2020-2022	0.077	0.077	-0.028**	-0.002	0.051	-0.054***	-0.054***	-0.054***
2021-2023	-0.002	0.057	0.051	0.133	-0.002	-0.053***	0.183*	0.106
2022-2024Q2	-0.054***	0.073*	0.037	0.177**	0.076	-0.047***	0.017	-0.053***

Notes: *,**,*** denote the level of significance of 10%, 5% and 1% levels, respectively. Robust standard deviations computed but omitted for reasons of parsimony.