Model-free and Model-based connectedness in highly, medium and lowly correlated financial returns: analyses of OECD inflations

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Model-free and Model-based connectedness in highly, medium and lowly correlated financial returns: analyses of OECD inflations[1]

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Abstract

This paper deals with the analysis of inflation in financial returns by using model-free connectedness framework which includes investigating persistence in the series and data from 22 countries from April 1958 to November 2023 which are grouped into highly, medium and lowly correlated returns. The results indicate that 10 countries, among the members of G12 are listed among highly-medium correlated inflation returns. The G7 countries are listed with high-medium inflation returns, of which France, Germany, Italy, and the USA are net shock transmitters, while Canada, Japan and the UK are net shock receivers. Total connectedness indices are positively related to the correlations, and the connectedness is found to increase astronomically towards late 2020 due to economic and financial market integration. Global financial crisis such as that of 2007-2009 and the COVID-19 pandemic have reset the integration of economic variables again. A policy recommendation is therefore given at the end.

Keywords: Persistence; fractional integration; model-free connectedness; price inflation, G12 countries
JEL Classification: C22; E31; C5; C6

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1. Introduction

The dynamic relationships between economic and financial variables and the mechanism of shock transmission are crucial to policymakers and asset market participants. Such a relationship provokes early risk assessments to forestall turbulence in economic and financial systems. More specifically, the ability to recognise, comprehend, and diversify underlying sources of risk and return in financial markets is one of the many reasons why the empirical analysis of the cross-section of stock returns is relevant (Fama and French, 1992; Christoffersen et al., 2014; Engle, 2016). Researchers can determine important drivers of returns, such as size, value, momentum, and quality, by looking at the returns of particular stocks (Fama and French, 1992; Carhart, 1997). Because it offers insights into both stock selection and portfolio construction, this information is crucial for both practitioners and researchers. In this regard, Diebold and Yılmaz (2012) ground-breaking research might be considered a turning point in the study of dynamic network spillovers and the unfavourable consequences of potentially contagious times.

In recent times, authorities have become interested in the synchronisation of inflation in various nations. As noted in the paper titled: “does the U.S. export inflation? Evidence from the dynamic inflation spillover between the U.S. and EAGLEs” by Nguyen et al. (2024), we could see that inflations shocks can actually transmit from the U.S. to other countries, spillover index rising to over 70% during extreme inflationary situations. A number of factors are thought to be significant for the international spillover of inflation, including the co-movement of business cycles internationally (Monacelli and Sala 2009; Mumtaz et al., 2011), persistence of inflation (Gil-Alana, et al., 2016; Yaya, 2018; Yaya, et al., 2019;), purchasing power parity internationally (Gefang 2008; Chang et al., 2010), technology spillover internationally (Henriksen et al., 2011), common economic shocks internationally (Neely and Rapach 2011), common monetary policies internationally (Tiwari et al., 2016), etc. In addition to knowing where inflation spillover originates, forecasting future business cycles also requires a solid grasp of the phenomenon. Countries may overestimate domestic progress if they do not have a solid understanding of the inflation spillover mechanism (Ciccarelli and Mojon, 2010). In the literature on macroeconomic and financial analysis, examining the problem of inflation spillover is crucial. In the wake of the COVID-19 pandemic, the G7 countries have implemented standard fiscal (tax cuts, business grant programmes, interest rate reduction policies, etc.) and monetary policies (decreasing interest rate policies, quantitative easing, etc.) that could lead to significant inflationary spillovers within this group of nations in the near future. As a result, the connectedness of inflations has gained increasing relevance.

Diebold and Yilmax (2012) is often referred to in the literature on dynamic connectedness methods for economic and financial assets. Other updated versions such as the Time-Varying Parameter – VAR (TVP-VAR) model of Antonakakis et al. (2020), and the Quantile-VAR model of Chatziantoniou, Gabauer, and Stenfors (2021), both in the time domain approach are being employed in financial modelling.[2] Variants of these are based on frequency connectedness, joint and extended joint connectedness (see Barunik et al., 2020; Chatziantoniou et al., 2022; Cunado et al., 2022).

Due to the numerous dynamic connectedness models and their variants, there is a need for a baseline dynamic model for the broader connectedness, while Diebold and Yilmax (2012) VAR connectedness renders static spillover effects which are limited in explaining macroeconomic dynamics.[3] Also, the model-based dynamic connectedness approach mentioned above breaks down when the number of variables is too large, and the computation speed slows down. In each of the dynamic connectedness model, Gabauer et al. (2023) has noted that the Generalized Forecast Error Variance Decomposition (GFEVD) reduces to the

[2] These, among others are model-based methods of dynamic connectedness.
[3] https://gabauerdavid.github.io/ConnectednessApproach/Rpackage

R^2 value in a simple regression case whenever VAR coefficients are not significant, leading to the relationship between the Pearson correlations and pairwise connectedness index. The normalization technique adopted for the GFEVD tends to overestimate or underestimate the effect of one variable on the other (see Balcilar et al., 2021; Lastrapes and Wiesen, 2021), Naeem, Chatziantoniou, Gabauer and Karim (2024) therefore propose the estimate of a multivariate regression model, where the variable i is chosen as a dependent variable and all other variables are independent instead of estimating $k-1$ bivariate regression models, to obtain R_{ij}^2 as in the model-free connectedness method of Gabauer et. al. (2023). The fact that the R^2 of a multivariate regression lies between 0 and 1 makes the row sum-unity standardisation redundant. The effect of an independent variable is then checked on the dependent variable using the Genizi (1993) R^2 decomposition connectedness framework which is unique as it combines the Diebold and Yilmax (2012) approach with the partial correlation network approach of Kenett et al. (2015), following the Genizi (1993) R^2 decomposition method. Thus, the model-free connectedness method seems like an improved version of the Diebold and Yilmax (2012) approach for dynamic connectedness that is capable of handling limitless number of variables due to its reliance on variances and covariances (Gabauer et al., 2023 and Naeem et al., 2024). The model-based methods of Antonakakis et al. (2020), Barunik et al. (2020), Chatziantoniou, Gabauer, and Stenfors (2021), Chatziantoniou et al. (2022) and Cunado et al. (2022) mentioned earlier are lacking in that regard. The model-based methods can lead to misleading decisions, while the model-free methods are more reliable due to their reliance on correlations between variables.

The present paper therefore employed the R^2 contemporaneous connectedness approach, that is, the model-free connectedness method to model the spillovers and transmission of shocks in price inflation of a group of 22 Organisation for Economic Cooperation and Development (OECD) countries. The data spanned from April 1958 to

November 2023. The list includes: Austria, Belgium, Canada, France, Germany, Japan, Luxembourg, Switzerland, Finland, Italy, Norway, Sweden, Greece, Iceland, Korea, Portugal, Spain, Turkey, India, United States of America, United Kingdom, and South Africa. Based on transformed log-returns, the countries are grouped in highly, medium and lowly correlated groups. We achieved this using Pearson correlations which is confirmed by the Principal Component Analysis (PCA) in order to create orthogonal groups. We checked for correlations and persistence of inflation returns in each group. We employed the model-free connectedness approach of Naeem, Chatziantoniou, Gabauer and Karim (2024) to unleash the time spillover relationships among the three PCA. The robustness of the results is checked against model-based connectedness frameworks such as the Diebold and Yilmax (2012) VAR method and the Time-Varying Parameter - VAR (TVP-VAR) method of Antonakakis et al. (2020).

Findings in the paper are striking as 10 countries in the G12 group fall into the category of high-medium inflation correlations. Total connectedness indices vary with correlation strengths, and in which correlations are positive in most cases, and in the case of weak correlations among variables for computations. We also unfold much stronger inflation connectedness in recent years as the connectedness, based on any correlation levels, have increased astronomically over time. Finally, there is a gain in the computational speed of model-free connectedness methods compared to model-based methods. In order to better handle inflation shocks and financial market disruptions, it is imperative that nations embrace cooperative frameworks, especially within the G7, G12, and EU, as the study finds net inflation shock transmitters and receivers. Understanding the localized economic determinants that may mitigate or exacerbate inflation transmission should receive particular emphasis for nations with weak correlations in inflation patterns, such as some emerging economies. Our findings will therefore interest policy makers in ways itemised above.

The remaining part of this paper is structured as follows: Section 2 describes the data and the methodology used based on alternative econometric models. Section 3 describe the main results while Section 4 is devoted to the conclusions.

2. Connectedness of Inflation

Inflation is an important economic variable that measures the financial state of wellbeing of an economy. Inflation connectedness therefore describes the ways in which changes in one country's inflation can affect or be affected by changes in inflation in other nations. In our increasingly globalised economy, the economic decisions and actions in one country can have a big impact on the entire world economy as noted in Nguyen et al. (2024). For instance, in most OECD countries in the last 40 years, inflation has reached an unprecedented level.[4] The supply linkages that span the globe can propagate inflation. For instance, the cost of commodities exported from a big producing nation may increase due to inflation, driving up prices in importing nations. Many nations rely on international markets for goods such as food, petrol, and oil. Global inflation may result from a rise in the price of these commodities, particularly in nations that rely significantly on imports (Smith, 2021). Global inflation may be impacted by the monetary policies of central banks, particularly in developed nations such as the US, the EU, and China. For example, the U.S. Federal Reserve's decision to raise interest rates in an attempt to curb domestic inflation may have an impact on global investment flows and currency values, which in turn may have an impact on inflation in other nations. Changes in exchange rates may cause inflation from imports. A nation's import costs will go up if its currency weakens compared to the currencies of its trading partners, which could lead to higher inflation. In terms of inflation, nations that are members of economic unions, such as the Eurozone, are closely related. Inflation in other member states can be directly impacted by the

[4] https://www.oecd.org/en/topics/sub-issues/inflation-and-cost-of-living.html

economic climate and policy decisions made in one member state. Inflation connectivity can also be facilitated by international financial markets (Johnson and Lee, 2022).

The expectations of investors regarding inflation can have an impact on bond yields and stock prices in various nations. Through modifications in the dynamics of supply and demand, political developments, economic policies, and stability in one nation can have an indirect impact on inflation by influencing investor's confidence and economic activity in other nations. The COVID-19 pandemic brought to light the interdependence of the world's economies. Global supply chain interruptions, changes in consumer behaviour, and government stimulus programmes in reaction to the pandemic have all had a major impact on inflation. Therefore, inflation connectivity emphasises how crucial it is to manage global economic difficulties through coordinated policy responses and international cooperation. It also emphasises how difficult it is to make economic policies in a globalised environment due to the fact that inflation is a core monetary policy instrument. Thus, the global economy is influenced when decisions made in one nation have a significant impact on other nations (see Nguyen et al., 2024).

Scant literature exists on the cross-spillovers and connectedness of inflation. Tiwari et al. (2018) use monthly consumer price index (CPI) based inflation data covering the period 1955M1 to 2017M4 to investigate the inflation spillover in a subset of Euro-area nations. The authors employed two newly created spillover techniques: the Diebold–Yilmaz (DY method), which operates in the time domain, and the Barunik–Krehlik (BK method), which operates in the frequency domain. They examine spillovers lasting 1-4 months and longer than 4 months. The research holds significance as the co-movement in global inflation rates might stem from various factors such as shared shocks, similarities in central bank response functions, global commerce, and the functioning of purchasing power parity theory. Nonetheless, it is essential to comprehend the inflation behaviour and formulation in order to evaluate the synchronisation of inflation variations among nations or regions. Using a dynamic factor model, Ha, Kose, and Ohnsorge (2019) examine the degree of global inflation synchronisation over a 50-year period in a wide range of nations. Thanks to their methodology, the authors are able to examine similarities in inflation synchronisation over a broad range of inflation metrics and take into consideration variations between groupings of countries (developed economies, emerging markets, and developing economies). Three main findings are presented in the paper. First, there has been a global synchronisation of inflation movements over time, with a common global factor accounting for around 22% of the variation in national inflation rates since 2001. Second, there has been a wider spread of inflation synchronisation. Over the past 20 years, inflation synchronisation has grown significantly in both emerging market and developing nations, while it was previously far more prominent in advanced economies. Furthermore, since 2001, inflation synchronisation has become noteworthy for all inflation measures, as opposed to its prior prominence for only those inflation measures that comprised primarily tradable items.

Khandokar et al. (2021) suggest that a number of recent global shocks, including as the renegotiation of NAFTA, the trade war between the United States and China, Brexit, and the COVID-19 epidemic, may have had an impact on the inflation spillover in the G7 countries. The impact of these significant occurrences on the G7 countries' inflation spillover is ignored in the research. It closes this gap and looks into the short-, medium-, and long-term characteristics of inflation spillover. Based on monthly data from 1956:6 to 2020:12, the study concludes that the primary sources of inflation are the United States and Japan. The inflation spillover is determined to be caused by low-cost technology, purchasing power parity, international trade, and the Abenomics strategy. Al-Nassar and Albahouth (2023) investigate how inflation spreads among the G20 economies and assess how much it affects inflation at home. We employ the Diebold and Yilmaz spillover technique to achieve this. Unconditional research yields data that show significant differences in advanced and emerging economies' inflation spillover patterns. Compared to their emerging counterparts, advanced countries are more vulnerable to global shocks due to higher rates of spillover. Notably, Yang et al. (2006) examined the inflation spillover in the G7 nations using a VAR technique for the years 1973–2003. Although Yang et al. (2006)'s forecast error variance decomposition analysis and impulse response functions demonstrate the dynamics of inflation spillover across time, the study ignored the characteristics of inflation spillover in other time periods.

None of this literature has considered the case of OECD inflation, in attempting to investigate the dynamic connectedness between inflation rates in prominent economies. Attempting this with the classical models such as TVP-VAR, QVAR, and other variants could result in breakdowns since these models are limited in the number of variables that can be included in the analysis. Also, a connection between model-based and model-free connectedness models, as applied to inflations here is another value addition.

3. Data and Econometric Methods

Data used in the paper are monthly Consumer Price Indices (CPIs) of 22 OECD countries spanning from April 1958 to November 2023, sampled based on availability. The countries are Austria (AUT), Belgium (BEL), Canada (CAN), France (FRA), Germany (DEU), Japan (JPN), Luxembourg (LUX), Switzerland (CHE), Finland (FIN), Italy (ITA), Norway (NOR), Sweden (SWE), Greece (GRC), Iceland (ISL), Korea (KOR), Portugal (PRT), Spain (ESP), Turkey (TUR), India (IND), United States of America (USA), United Kingdom (GBR), and South Africa (ZAF). These were obtained from the database of the organization at https://data.oecd.org/price/inflation-cpi.htm. CPIs are all nonstationary based on the fact that they are prices, nevertheless, Elliott et al.'s (ERS, 1996) unit root test confirmed the nonstationarity. Similar evidence is obtained with other unit root procedures (Dickey and Fuller, ADF, 1979; Phillips and Perron, PP, 1988). Thus, stationarity equivalent series are required, and these are obtained as log-transformed version of CPIs expressed in percentages: $y_{it} = 100 \times \{\log(CPI_t) - \log(CPI_{t-1})\}$ where CPI_{t-1} are the CPIs in previous months and CPI_t are the current month CPIs.[5]

Correlation analysis was carried out on group correlations in inflation returns (change in CPIs) into high, medium and low as presented in Table 1. This is necessary in order to check the effect of correlation strength with the model-free connectedness, and this will make the findings more robust. The groupings of correlations are also checked with the factor analysis via principal component analysis and these agree. Interestingly, five members of the Group of Seven economies (G7) are found in the list of highly correlated inflation returns. These are Canada (CAN), France (FRA), Germany (DEU), Japan (JPN), and the USA. By extending this list to cover G12 nations, Belgium (BEL) and Switzerland (SWE) are added. Due to regulations in international economies and financial states of the G12 countries (Riggan, 2009), it is expected, and as found in this paper, similar to G7 that their inflation returns will be highly or medium correlated as grouped

INSERT TABLE 1 ABOUT HERE

3.1 Persistence tests

Apart from correlation which infers interdependencies between the variables, there is the need to test for cross-interdependency by means of persistence tests. Persistence informs long-term correlations across different scales as this reveals hidden patterns, trends, and relationships in the multiple variables. We offer an estimate of d for persistence in the context of parametric methods that was created by Robinson (1994). This estimate is highly generic and useful for

[5] Note, y_{it} is used as a proxy for inflation rate since it is erroneous to difference inflation rates as returns series. Thus, CPIs fit in this regard.

the current study. By assuming that each inflation returns, y_t, t = 1, 2, …, is estimated based on the equation:

$$y_t = \beta_0 + \beta_1 t + x_t \qquad t = 1,2, \ldots, \tag{1}$$

where β_0 and β_1 are the parameters for the intercept and a linear trend, and x_t is characterized by the fractional integration model,

$$(1 - \mathrm{B})^d x_t = u_t \qquad t = 1,2, \ldots, \tag{2}$$

with d being a real number value representing the number of time series differences required to obtain a stationary series, i.e., $I(0)$, B is the lag backwardshift operator and u_t is the residual of the model which is assumed to be an $I(0)$ series. Table 2 displays the estimates of d along with the confidence bands corresponding to the non-rejection values of d at the 95% level for each of the series for each group.

INSERT TABLE 2 ABOUT HERE

The results can be summarized as follows:

For high correlation: All the estimates of d are significantly positive except for Austria where the I(0) hypothesis cannot be rejected; the highest estimates of d are obtained for France (d = 0.38), and Belgium and Canada (d = 0.31). There are three countries, Austria, Japan and Switzerland, where the time trend coefficient is found to be significantly negative.

For medium correlation: All the estimates of d are significantly positive with values ranging from 0.23 (Norway) and 0.26 for Sweden to 0.47 in the case of Italy. For Great Britain, the value is 0.34 and for Finland, 0.35. There are no significant trends for these countries.

For low correlation: For India and Korea the null hypothesis of short memory, i.e., d = 0 cannot be rejected. In all other cases, d is significantly positive, the highest value obtained for ISL (Island) with d = 0.42. Turkey and South Africa also display large values with d = 0.35 and 0.32, respectively. The time trend coefficient is found to be significantly negative for the cases of Spain, Korea and Portugal.

The results of persistence presented in Table 2 are in long memory range even though some are not significant, which further confirms the long range dependency in inflation series (Gil-Alana et al., 2012). Though, within each group (high, medium or low correlation), the persistence levels are not related, even though correlations are related to persistence. This is possible probably due to high volatility in the monthly inflation returns. This disagreement between correlation strengths and persistence further add more ingredients to our findings on inflation returns connectedness using model-free approaches, discussed below.

3.2 Model-free connectedness approach

Diebold and Yilmax (2012) set up a VAR model (hereafter DY) of lag order p, defined as,

$$y_t = \sum_i^p B_i y_{t-i} + u_t, \qquad u_t \sim N(0, \Sigma), \tag{3}$$

where y_t and y_{t-i} are $k \times 1$ dimensional vectors of endogenous variables and $i = 1, \ldots, p$, and u_t is a $k \times 1$ dimensional error vector. B and Σ are $k \times k$ dimensional coefficient and variance-covariance matrix for VAR. Re-writing the VAR in (3) in Wold's representation facilitates the computation of the H-step-ahead generalized forecast variance decomposition (GFEVD). Thus, the GFEVD for the VAR setup demonstrates the amount of j variable that is contributed to the forecast error variance of variable i (see Koop et al., 1996; Pesaran and Shin, 1998). By allowing for the parameter B_i $(i = 1, \ldots, p)$ to be time-varying as in B_{it} and $u_t \sim (0, \Sigma_t)$, with further simplification of Antonakakis et al. (2020). The GFEVD for VAR is then denoted as $\theta_{ij}^{gen}(H)$. The total connectedness (TCI) is defined as follows:

$$TCI(H) = \frac{\sum_{ij,j=1,i\neq j}^{k} \tilde{\theta}_{ij}^{gen}(H)}{k}, \tag{4}$$

where $\tilde{\theta}_{ij}^{gen}(H)$ is the scaled GFEVD obtained as $\tilde{\theta}_{ij}^{gen}(H) = \frac{\theta_{ij}^{gen}(H)}{\sum_{l=1}^{k} \theta_{ij}^{gen}(H)}$, *w*here TCI is the strength of a variable j on all other variables i of the strength of all other variables i on a variable j such that low TCI implies low network interconnectedness (low market risk) and vice-versa.

The VAR GFEVD in (7) shown in Gabauer et al. (2023) as,

$$\tilde{\theta}_{ij}^{gen}(H) = \left(\frac{\Sigma_{ij}}{\sqrt{\Sigma_{jj}\Sigma_{ii}}} \right)^2 = \rho_{ij}^2 = R_{ij}^2 \ . \quad (5)$$

We assume that the lagged variables y_{t-p} $(i = 1, \dots, p)$ have no influence on y_t implying that the VAR coefficients B are zeroed. $\tilde{\theta}_{ij}^{gen}(H)$ is now the R^2 goodness-of-fit in the bivariate linear regression between variable i and j (i.e. squared Pearson correlation), and here R_{ij}^2 is invariant to the forecast horizon H. Then, by using normalization, the obtained scaled GFEVD is formulated as,

$$\tilde{\theta}_{ij}^{gen}(H) = \frac{R_{ij}^2}{\sum_{l=1}^{k} R_{il}^2} \quad (6)$$

$\sum_{j=1}^{k} \tilde{\theta}_{ij}^{gen}(H) = 1$ and $\sum_{i,j=1}^{k} \tilde{\theta}_{ij}^{gen}(H) = k$, i.e. the row sum of variable i equal 1 when variable i is perfectly predicted by all other variables j that are orthogonal to each other. The TCI which is the average sum of weighted R_{ij}^2 $(i \neq j)$ is then simplified as,

$$TCI = \frac{1}{k}\sum_{i=1}^{k} \tilde{\theta}_{ij}^{gen}(H) \ = 1 - \frac{1}{k}\sum_{i=1}^{k} \tilde{\theta}_{ii}^{gen}(H) \ = 1 - \frac{1}{k}\sum_{i=1}^{k} \frac{R_{ij}^2}{\sum_{l=1}^{k} R_{il}^2} \ , \quad (7)$$

value and with the fact that $R_{il}^2 = 1$ and the maximum value of $\sum_{l=1, l \neq i}^{k} R_{il}^2 = k$, then,

$$TCI = 1 - \frac{1}{k}\sum_{i=1}^{k} \frac{1}{k} = \frac{k-1}{k} \ . \quad (8)$$

Thus, TCI is bounded between 0 and $\frac{k-1}{k}$.

Balcilar et.al (2021) and Lastrapes and Wiesen (2021) show the sub-optimality of the normalization technique in overestimating or underestimating the spillover effect of variable j on variable i. To overcome this deficiency, Naeem, Chatziantoniou, Gabauer and Karim (2024) estimate a multivariate regression model where i variable is chosen as a dependent variable and all other variables are independent instead of estimating $k-1$ bivariate regression models to obtain R_{ij}^2 as in the model-free connectedness of Gabauer et. al. (2023). Based on the contemporaneous model-free connectedness approach of Naeem et. al. (2024), R_i^2 goodness of fit measure was obtained in the interval (0,1). Having estimated k multivariate linear regression models,

$$y_t = Bx_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma), \tag{9}$$

where $k \times k$ are coefficient matrices, B is a parameter driving x_t with y_t and it has zeros in its diagonal. Based on Genizi (1993) decomposition method, R^{2_G} is set as an illustration for R^2 contribution vectors with the sum of this vector equaling R^2 goodness-of -fit measure of the corresponding multiple regression model R_i^2. Thus, the spillover effect of variable j on the R^2 goodness-of-fit measure of i is given based on the GFEVD,

$$\tilde{\theta}_{ij}^{cont}(H) = \frac{R_{ij}^{2_G}}{\sum_{l=1}^{k} R_{il}^{2_G}} \tag{10}$$

such that both $R_{ij}^{2_G}$ and $\frac{R_{ij}^{2_G}}{\sum_{l=1}^{k} R_{il}^{2_G}}$ are used as GFEVD $\tilde{\theta}_{ij}(H)$ in computing the connectedness measure.

The corresponding TCI and NET measures are then obtained using the fact that R_{ij}^{2G} lies within 0 and 1.

$$TCI = \frac{1}{k}\sum_{i=1}^{k} R_{ij}^{2G}. \tag{11}$$

The TCI measures market risk, as higher value of it implies high market risk, and its low value implies low market risk. For NET connectedness, $FROM_i = \sum_{i=1}^{k} R_{ij}^{2G}$, $TO_i = \sum_{i=1}^{k} R_{ji}^{2G}$, and,

$$NET_i = TO_i - FROM_i\ , \tag{12}$$

where TO_i and $FROM_i$ give the proportion of shocks in the dependent variable j that is explained by all other variables i, and the proportions of shocks in all variables i that is explained by variable j, respectively. Correspondingly, these are the amount of shocks transmitted from variable j to variabes i (TO) and the amount of shocks received from j by i $(FROM)$. If the $NET_i > 0$, it suggests that variable i is a net shock transmitter in the connectedness, otherwise it is a net shock receiver.

4. Results and Discussion

4.1 Average connectedness results

Tables 3a,b, 4a,b, and 5a,b present the results of average connectedness for model-free (Pearson, Spearman, and Kendal correlations), Diebold-Yilmax (DY), and TVP-VAR. In Tables 3a, 4a, and 5a for model-free connectedness, the diagonal elements, connoting own-variance spillovers in the case of VAR and TVP-VAR (Tables 3b, 4b, and 5b) are zeroed. This is mentioned earlier as the contribution of the contemporaneous model-free approach of Naeem et al. (2024) over the model-free connectedness approach of Gabauer et al. (2023), which is based on the VAR model of Diebold ad Yilmax (2012). In Table 3a, the results of net directional connectedness based on Pearson, Spearman and Kendall correlations present Austria, Canada, Japan, Luxembourg and Switzerland as net shock receivers. The only exception is the Pearson correlation connectedness that renders the German inflation as a net shock receiver, while Spearman and Kendall correlations render the inflation series as net shock transmitter. Thus, Belgium, France, Germany, and the USA are net shock transmitters. In these results, the TCI for the Kendal method is 41.23 which is a bit higher than that of Pearson and Spearman (about 37). France, Germany and the USA are three G7 members in this list of high correlated inflations that are net shock transmitters, while Canada, and Japan, two members of the G7 group, are net shock receivers.

Results of connectedness based on DY VAR, and TVP-VAR in Table 3b agree with those reported in Table 3a, while TCI are marginally higher in Table 3b compared to those reported in Table 3a.

INSERT TABLES 3a, 3b ABOUT HERE

In Tables 4a, and 4b, the results of medium correlated inflation returns for five countries (Finland, Italy, Norway, Sweden and the United Kingdom), are presented for model-free and model-based methods, respectively. The remaining two members of G7, that is, Italy and the United Kingdom are found in this list. One can conclude that G7 inflations returns are correlated. Here, inflation rates of these two countries are net shock receivers with NET values -0.18 and -0.92, respectively for Pearson correlation connectedness while for Spearman and Kendall correlation connectedness, Italy is a net shock transmitter and the UK is a net shock receiver. Consistently, Norway is a net shock receiver (see Table 4a). In Table 4b, Norway, Sweden and Great Britain are net shock receivers based on DY and TVP-VAR connectedness methods, while Great Britain is a strong net receiver of shocks. Similarly, Italy is a strong net transmitter of shock. Thus, results in Table 4b (model-based methods) confirmed those obtained in Table 4a (Pearson, Spearman, and Kendall).

In sum, by relating the findings in Tables 3a, 3b, 4a, and 4b, one can find that the G7 countries are among countries with high-medium inflation returns of which France, Germany, Italy, and the USA are net shock transmitters, while Canada, Japan and the UK are net shock receivers. By extending the list to G12 at this juncture, Belgium, France, Germany, USA, and Sweden are net inflation shock transmitters, while Canada, Japan, Switzerland, Italy, and the United Kingdom are net shock receivers. Recall, G12 or G7 are countries whose central banks cooperate for international economic and financial regulations (Riggan, 2009).

INSERT TABLES 4a, 4b ABOUT HERE

The TCIs for highly correlated returns (see Tables 3a and 3b) are higher than corresponding TCIs for medium correlated returns (see Tables 4a and 4b). Thus, correlations in variables are related to connectedness as noted initially in Gabauer et al. (2023).

For low correlated returns (Tables 5a and 6a). The countries in this group are Greece, Iceland, Korea, Portugal, Spain, Turkey, India and South Africa of which Spain is a member of the G12 mentioned earlier. The inflation return series for Spain is lowly correlated with inflation returns of other countries listed here in Table 5a. Based on Pearson correlations connectedness, Portugal and Spain are net inflation shock transmitters, while Greece, Iceland, Korea, Turkey, India and South Africa are net shock receivers. By comparing the results by Spearman and Kendall correlations with that of Pearson correlation, there are agreement in net directional connectedness of inflations except in the case of Greece where Spearman and Kendall indicate Greece as a net inflation shock transmitter while Pearson indicates it as a net shock receiver. Based on the results in Table 5b, Greece is detected as a net shock transmitter by the DY connectedness method, and TVP-VAR method detects it as a net shock receiver. Further, most NET results based on the two methods (DY and TVP-VAR) do not agree with each other in their net shocks directions. For example, the DY connectedness method has Iceland as a net inflation shock transmitter while TVP-VAR has it as a net shock receiver. This inconsistency is found for Korea, Portugal, Spain, Turkey and India. This inconsistency appears in the case of low correlated inflation returns. This further shows the under-performance of DY VAR and TVP-VAR connectedness methods when there are weak correlations between variables used in the connectedness network.

INSERT TABLES 5a, 5b ABOUT HERE

4.2 Total and Net dynamic directional connectedness plots

Results presented so far are averages of total (TCI) and net (NET) connectedness which give the general overview (dominant directions) of connectedness. We present in Figure 1 plots of total connectedness for model-free (Pearson, Spearman and Kendall methods), and model-based connectedness (TVP-VAR and DY methods) highly correlated inflation returns. Pearson connectedness is in the black region, Spearman connectedness is given by the red line, and that of Kendall correlation method is indicated in green. Over the historic period for the three plots, TCIs for Kendall are the highest. Further, inflation rates become more connected, particularly during late 80s and late 90s. After 2010, they become more connected again, more so than the level in 80s-90s. The TVP-VAR TCI plot is similar to that of model-free connectedness methods. Net directional connectedness plots, given in Figure 2, also indicate the agreement in the historical directions of spillovers over time by the model-free and model-based methods.

INSERT FIGURE 1 ABOUT HERE

INSERT FIGURE 2 ABOUT HERE

INSERT FIGURE 3 ABOUT HERE

INSERT FIGURE 4 ABOUT HERE

INSERT FIGURE 5 ABOUT HERE

INSERT FIGURE 6 ABOUT HERE

Similar plots pattern of TCIs for medium (Figure 3) and lowly (Figure 5) correlated inflation returns are found, compared to that of highly correlated inflation returns in Figure 1. Inflations are generally becoming more linked as indicated in the astronomic increasing TCIs for model-free (Pearson, Spearman and Kendal) and TVP-VAR methods. Both model-free and model-based methods also agree in their net directional plots given in Figures 4 and 6 with some exceptions in the case of lowly correlated inflation returns connectedness due to weak correlations between returns as earlier observed in Table 5b.

5. Conclusions

The normalization technique often adopted for the generalized forecast error variance decomposition (GFEVD) during dynamic connectedness of causal variables economic as well as the limited number of variables included as inputs during estimation has led to the development of model-free connectedness methods as rival alternatives to model-based types.

Motivated by the above, we consider the model-free approach, that is, the R^2 contemporaneous connectedness method in modelling the spillovers and transmission of shocks in price inflation of a group of 22 OECD countries (Austria, Belgium, Canada, France, Germany, Japan, Luxembourg, Switzerland, Finland, Italy, Norway, Sweden, Greece, Iceland, Korea, Portugal, Spain, Turkey, India, United States of America, United Kingdom, and South Africa). We analyse monthly datasets, spanning from April 1958 to November 2023. Based on log-transformed differences of price inflations, we group countries into highly, medium and lowly correlated returns.

In the results, it is striking to observe that 10 countries, among members of G12 countries are listed among high-medium correlated inflation returns. France, Germany, and the USA, among highly correlated inflations, emerged as net inflation shock transmitters, while Canada, and Japan are net shock receivers in the correlation group. By combining high and low correlation groups, we find that G7 countries are listed with high-medium inflation returns, of which France, Germany, Italy, and the USA are net shock transmitters, while Canada, Japan and the UK are net shock receivers. Extending this to the full G12 list, Belgium, France, Germany, the USA and Sweden are net inflation shock transmitters, while Canada, Japan, Switzerland, Italy, and the United Kingdom are net shock receivers. This is expected as the ties between G7 or G12 nations account for international economic and financial regulations of their central banking (Riggan, 2009). Spain, a member of the G12 countries, found in the low inflation correlation group, is a net inflation shock transmitter. Portugal, a non-member of the

G12 is the second net inflation shock transmitter, while the rest, Greece, Iceland, Korea, Turkey, India, and South Africa are net inflation shocks receivers.

Total connectedness indices are positively related to the correlations and the connectedness is found to increase astronomically towards late 2020 due to economic and financial market integrations. As noted in Coskun et al. (2023), the global financial crisis such as the 2007-2009, and the COVID-19 pandemic crisis of 2020 have further reset the integration of economic variables causing market to be more integrated. In the case of lowly correlated inflations, inconsistency is found in their net shock directions due to weak correlations between variables and this further shows the under-performance of the Diebold-Yilmax VAR, and TVP-VAR connectedness methods, particularly when there is weak correlations between variables in the network.

As the study identifies net inflation shock transmitters and receivers, it is crucial for countries to adopt collaborative frameworks, particularly within the G7, G12, and EU, to address inflation shocks and financial market disruptions more effectively. For countries with weak correlations in inflation patterns, such as some emerging economies, special attention should be given to understanding the localized economic factors that might buffer or amplify inflation transmission. These countries may benefit from tailored policy interventions that address specific inflation drivers rather than adopting broad-based approaches suited for highly integrated economies.

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Table 1: Correlation groups (High, medium, and low)

High correlations								
	AUT	BEL	CAN	FRA	DEU	JPN	LUX	CHE
BEL	0.716							
CAN	0.598	0.729						
FRA	0.626	0.704	0.677					
DEU	0.776	0.826	0.703	0.675				
JPN	0.530	0.656	0.547	0.645	0.686			
LUX	0.654	0.708	0.637	0.706	0.742	0.596		
CHE	0.730	0.797	0.713	0.670	0.885	0.670	0.752	
USA	0.664	0.781	0.815	0.726	0.775	0.650	0.695	0.788
Medium correlations								
	FIN	ITA	NOR	SWE				
ITA	0.528							
NOR	0.478	0.348						
SWE	0.515	0.476	0.531					
GBR	0.526	0.516	0.355	0.447				
Low correlations								
	GRC	ISL	KOR	PRT	ESP	TUR	IND	
ISL	0.281							
KOR	0.053	0.166						
PRT	0.283	0.273	0.108					
ESP	0.289	0.358	0.130	0.336				
TUR	0.279	0.111	0.006	0.141	0.105			
IND	-0.075	0.084	-0.033	-0.056	-0.018	-0.010		
ZAF	0.178	0.231	0.051	0.223	0.224	0.215	0.141	

Table 2: Estimates of d on returns series based on Robinson (1994) approach for autocorrelated disturbances

Country	No terms	With a constant	With a constant and a linear time trend
i) High correlation			
AUT	0.04 (0.00, 0.10)	0.04 (0.00, 0.09)	**0.00 (-0.04, 0.06)**
BEL	0.32 (0.27, 0.38)	**0.31 (0.25, 0.37)**	0.31 (0.26, 0.37)
CAN	0.32 (0.27, 0.38)	**0.31 (0.26, 0.37)**	0.30 (0.25, 0.37)
CHE	0.24 (0.19, 0.30)	0.22 (0.17, 0.29)	**0.17 (0.11, 0.25)**
DEU	0.22 (0.17, 0.30)	**0.20 (0.15, 0.28)**	0.19 (0.13, 0.28)
FRA	0.41 (0.36, 0.46)	**0.38 (0.34, 0.44)**	0.33 (0.31, 0.42)
JPN	0.20 (0.17, 0.25)	0.19 (0.15, 0.24)	**0.13 (0.08, 0.18)**
LUX	0.26 (0.21, 0.32)	**0.25 (0.20, 0.31)**	0.25 (0.19, 0.31)
USA	0.29 (0.24, 0.36)	**0.29 (0.23, 0.36)**	0.29 (0.23, 0.36)
ii) medium correlation			
Country	No terms	With a constant	With a constant and a linear time trend
FIN	0.37 (0.33, 0.43)	**0.35 (0.31, 0.42)**	0.33 (0.29, 0.41)
GBR	0.35 (0.30, 0.41)	**0.34 (0.29, 0.40)**	0.33 (0.28, 0.40)
ITA	0.47 (0.43, 0.53)	**0.47 (0.42, 0.53)**	0.47 (0.41, 0.53)
NOR	0.25 (0.21, 0.31)	**0.23 (0.19, 0.29)**	0.21 (0.17, 0.27)
SWE	0.27 (0.23, 0.32)	**0.26 (0.21, 0.31)**	0.24 (0.18, 0.29)
USA	0.29 (0.24, 0.36)	0.29 (0.23, 0.36)	0.29 (0.23, 0.36)
iii) Low correlation			
Country	No terms	With a constant	With a constant and a linear time trend
ESP	0.27 (0.23, 0.31)	0.25 (0.21, 0.29)	0.22 (0.18, 0.27)
GRC	0.15 (0.12, 0.20)	0.15 (0.12, 0.19)	0.14 (0.11, 0.18)
IND	0.08 (-0.01, 0.18)	0.08 (-0.01, 0.20)	0.08 (-0.01, 0.20)
ISL	0.43 (0.38, 0.49)	0.42 (0.37, 0.48)	0.42 (0.36, 0.49)
KOR	0.11 (0.06, 0.16)	0.09 (0.05, 0.14)	**-0.03 (-0.09, 0.03)**
PRT	0.21 (0.17, 0.26)	0.20 (0.16, 0.24)	0.18 (0.15, 0.23)
TUR	0.36 (0.30, 0.41)	0.35 (0.30, 0.41)	0.35 (0.30, 0.41)
ZAF	0.32 (0.28, 0.37)	0.32 (0.27, 0.37)	0.33 (0.28, 0.38)

Table 3a: Model-free connectedness for high correlated returns

Pearson Correlations Connectedness										
	AUT	BEL	CAN	FRA	DEU	JPN	LUX	CHE	USA	FROM
AUT	0.00	5.68	1.98	5.93	9.47	2.69	3.02	4.17	1.49	34.44
BEL	5.41	0.00	4.36	6.88	6.97	2.26	6.23	1.71	7.27	41.09
CAN	2.01	4.44	0.00	5.77	0.82	0.82	1.85	1.69	19.28	36.67
FRA	5.50	6.65	5.32	0.00	4.41	5.52	11.47	4.46	8.91	52.25
DEU	9.41	7.24	0.87	4.91	0.00	1.59	5.41	4.87	1.74	36.03
JPN	2.86	2.58	0.98	6.29	1.77	0.00	1.49	1.76	5.37	23.12
LUX	3.09	6.36	1.86	12.69	5.48	1.42	0.00	3.87	1.97	36.74
CHE	4.27	1.80	1.66	4.83	5.21	1.70	3.84	0.00	4.07	27.40
USA	1.44	6.92	18.08	9.26	1.66	4.54	1.91	3.80	0.00	47.60
TO	33.98	41.66	35.11	56.56	35.81	20.53	35.22	26.34	50.11	335.32
Inc.Own	33.98	41.66	35.11	56.56	35.81	20.53	35.22	26.34	50.11	TCI
NET	-0.45	0.58	-1.56	4.30	-0.22	-2.58	-1.52	-1.05	2.51	37.26
Spearman Correlations Connectedness										
	AUT	BEL	CAN	FRA	DEU	JPN	LUX	CHE	USA	FROM
AUT	0.00	5.21	2.39	4.46	8.63	2.56	3.28	5.20	1.82	33.55
BEL	5.00	0.00	4.21	5.75	9.08	1.83	6.79	1.74	5.69	40.07
CAN	2.43	4.28	0.00	5.79	0.79	0.90	3.33	1.79	18.41	37.73
FRA	4.29	5.57	5.37	0.00	4.14	5.83	11.97	4.47	8.53	50.18
DEU	8.53	9.36	0.82	4.53	0.00	1.91	4.74	5.74	1.62	37.24
JPN	2.77	2.10	1.02	6.60	2.15	0.00	1.66	1.57	5.31	23.17
LUX	3.33	6.87	3.31	12.60	4.77	1.56	0.00	5.81	2.42	40.67
CHE	5.22	1.80	1.73	4.70	6.13	1.47	5.88	0.00	4.51	31.44
USA	1.78	5.50	17.49	8.75	1.56	4.66	2.39	4.26	0.00	46.38
TO	33.35	40.68	36.33	53.18	37.25	20.73	40.04	30.57	48.30	340.43
Inc.Own	33.35	40.68	36.33	53.18	37.25	20.73	40.04	30.57	48.30	TCI
NET	-0.20	0.61	-1.39	3.00	0.01	-2.45	-0.63	-0.87	1.92	37.83
Kendall Correlations Connectedness										
	AUT	BEL	CAN	FRA	DEU	JPN	LUX	CHE	USA	FROM
AUT	0.00	5.57	2.54	5.19	9.74	2.78	3.48	5.60	1.99	36.89
BEL	5.33	0.00	4.60	6.55	9.78	2.11	7.43	2.07	6.08	43.94
CAN	2.58	4.69	0.00	5.90	0.96	1.13	3.85	2.10	20.21	41.43
FRA	4.97	6.33	5.44	0.00	4.43	6.45	12.06	4.66	9.35	53.69
DEU	9.58	10.09	1.01	4.85	0.00	2.22	5.22	6.30	1.85	41.11
JPN	3.03	2.45	1.30	7.34	2.53	0.00	1.96	1.75	5.93	26.29
LUX	3.55	7.56	3.84	12.77	5.29	1.83	0.00	5.97	2.55	43.36
CHE	5.66	2.15	2.04	4.91	6.78	1.62	6.04	0.00	4.73	33.92
USA	1.94	5.87	19.13	9.60	1.79	5.15	2.52	4.44	0.00	50.43
TO	36.63	44.71	39.89	57.11	41.29	23.29	42.57	32.89	52.69	371.07
Inc.Own	36.63	44.71	39.89	57.11	41.29	23.29	42.57	32.89	52.69	TCI
NET	-0.26	0.77	-1.54	3.42	0.18	-3.00	-0.79	-1.04	2.26	41.23

Table 3b: Model-based connectedness for high correlated returns

DY Connectedness										
	AUT	BEL	CAN	FRA	DEU	JPN	LUX	CHE	USA	FROM
AUT	60.72	7.00	1.96	6.99	8.03	2.53	5.22	4.59	2.96	39.28
BEL	5.94	53.98	4.74	9.00	6.07	3.87	4.43	3.37	8.69	46.10
CAN	1.51	8.39	50.89	10.03	3,23	1.44	4.30	2.12	18.09	49.11
FRA	3.44	9.87	8.00	47.55	5.30	5.57	7.91	3.26	9.09	52.45
DEU	6.33	7.93	1.82	6.62	58.34	2.03	5.65	7.05	4.22	41.66
JPN	3.52	5.12	2.37	7.82	3.90	66.94	0.78	6.32	4.02	33.06
LUX	3.65	10.51	3.88	9.47	5.25	2.22	52.94	5.49	6.58	46.06
CHE	1.58	4.57	4.26	5.14	5.87	4.67	5.13	62.17	6.61	37.83
USA	2.52	9.21	14.25	10.87	5.95	1.72	3.03	2.54	49.91	50.09
TO	28.48	62.60	41.28	65.13	43.5	24.05	36.45	34.76	60.27	296.62
Inc.Own	89.20	116.50	92.17	112.67	101.94	91.00	89.39	96.93	110.19	TCI
NET	-10.80	16.50	-7.83	12.69	1.94	-9.00	-10.61	-3.07	10.19	44.07
Time-Varying Parameter-VAR Connectedness										
	AUT	BEL	CAN	FRA	DEU	JPN	LUX	CHE	USA	FROM
AUT	46.43	9.78	4.39	8.82	10.13	2.47	6.94	7.10	3.94	53.57
BEL	7.29	46.80	6.50	9.07	7.55	4.00	5.77	3.88	9.15	53.20
CAN	4.02	10.43	42.73	8.63	4.47	3.49	5.16	5.01	16.06	57.27
FRA	7.12	10.99	5.91	40.52	6.24	7.08	7.95	5.48	8.71	59.48
DEU	9.22	10.12	2.90	7.94	50.17	3.62	5.61	5.94	4.48	49.83
JPN	4.09	5.84	3.77	11.53	4.25	55.46	3.93	5.12	6	44. 54
LUX	6.71	10.29	3.72	10.80	6.49	4.49	45.06	7.13	5.31	54.94
CHE	4.84	6.10	5.43	8.52	6.72	6.40	6.50	47.72	7,77	52.28
USA	3.49	11.31	11.25	9.34	5.17	4.66	5.09	5.86	44.03	55.97
TO	46.78	74.86	43.89	74.64	51.01	36.03	6.94	45.53	61.40	481.97
Inc.Own	93.21	121.66	86.62	115.17	101.18	91.48	92.00	93.25	105,33	TCI
NET	-6.79	21.66	-13.38	15.17	1.18	-8.52	-8.52	-6.75	5.44	53.45

Table 4a: Model-based connectedness for medium correlated returns

Pearson Correlations Connectedness						
	FIN	ITA	NOR	SWE	GBR	FROM
FIN	0.00	5.92	7.80	11.66	8.66	34.03
ITA	6.06	0.00	2.03	6.75	5.76	20.60
NOR	8.26	1.99	0.00	11.36	1.66	23.27
SWE	11.42	6.73	10.41	0.00	7.81	36.37
GBR	8.99	5.78	1.62	8.41	0.00	24.81
TO	34.73	20.42	21.86	38.18	23.89	139.09
Inc.Own	34.73	20.42	21.86	38.18	23.89	TCI
NET	0.69	-0.18	-1.41	1.81	-0.92	27.82
Spearman Correlations Connectedness						
	FIN	ITA	NOR	SWE	GBR	FROM
FIN	0.00	6.45	8.05	12.38	9.13	36.01
ITA	6.45	0.00	2.60	6.68	7.49	23.23
NOR	8.47	2.58	0.00	12.33	1.94	25.34
SWE	11.98	6.78	11.31	0.00	8.28	38.35
GBR	9.40	7.52	1.89	8.88	0.00	27.68
TO	36.31	23.34	23.85	40.27	26.85	150.61
Inc.Own	36.31	23.34	23.85	40.27	26.85	TCI
NET	0.29	0.11	-1.48	1.92	-0.83	30.12
Kendall Correlations Connectedness						
	FIN	ITA	NOR	SWE	GBR	FROM
FIN	0.00	6.92	8.84	13.64	9.93	39.33
ITA	6.91	0.00	2.95	7.15	8.42	25.42
NOR	9.31	2.91	0.00	13.22	2.37	27.81
SWE	13.14	7.23	12.07	0.00	8.88	41.31
GBR	10.23	8.37	2.30	9.51	0.00	30.42
TO	39.59	25.43	26.15	43.52	29.61	164.30
Inc.Own	39.59	25.43	26.15	43.52	29.61	TCI
NET	0.25	0.00	-1.66	2.21	-0.81	32.86

Table 4b: Model-based connectedness for medium correlated returns

DY Connectedness						
	FIN	ITA	NOR	SWE	GBR	FROM
FIN	69.57	14.00	5.95	4.74	5.74	30.43
ITA	8.26	79.83	3.38	4.93	3.60	20.17
NOR	5.47	7.90	75.45	8.65	2,52	24.55
SWE	6.27	11.90	8.46	69.91	3.45	30.09
GBR	12.63	14.56	4.98	6.08	61.76	38.24
TO	32.63	48.37	22.77	24.20	15.31	143.48
Inc.Own	102.19	128.21	98.22	94.31	77.07	TCI
NET	2.19	28.21	-1.78	-5.69	-22.99	28.70
Time-Varying Parameter-VAR Connectedness						
	FIN	ITA	NOR	SWE	GBR	FROM
FIN	57.25	15.72	7.22	10.55	9.26	42.75
ITA	13.69	63.31	4.50	9.56	8.95	36.69
NOR	10.26	8.44	66.05	10.65	4.60	33.95
SWE	12.09	12.44	9.43	57.24	8.81	42.76
GBR	12.41	15.47	4.63	9.27	58.23	41.77
TO	48.45	52.07	25.78	40.03	31.61	197.93
Inc.Own	105.70	115.37	91.83	97.27	89.83	TCI
NET	5.70	15.37	-8.17	-2.73	-10.17	39.59

Table 5a: Model-free connectedness for low correlated returns

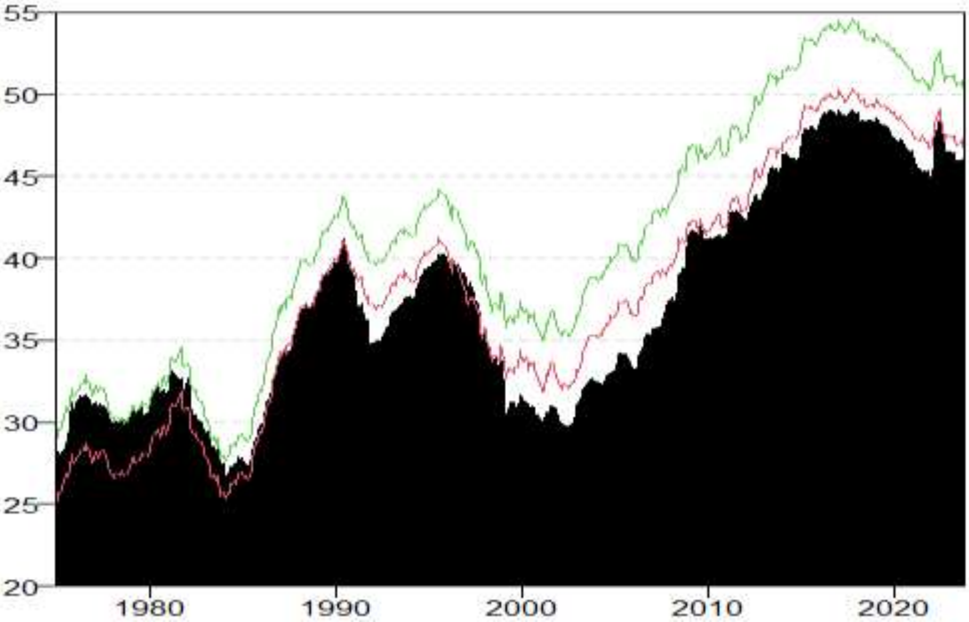
Pearson Correlations Connectedness									
	GRC	ISL	KOR	PRT	ESP	TUR	IND	ZAF	FROM
GRC	0.00	2.91	0.41	8.78	3.84	3.79	1.15	0.70	21.59
ISL	2.95	0.00	0.83	3.26	4.63	2.68	0.89	1.02	16.26
KOR	0.52	0.88	0.00	1.44	1.27	0.87	0.59	2.26	7.82
PRT	8.39	3.05	1.22	0.00	12.20	0.86	1.31	2.59	29.62
ESP	3.77	4.29	1.16	12.69	0.00	0.93	0.40	2.22	25.46
TUR	3.84	2.77	0.86	0.90	1.00	0.00	0.70	1.16	11.21
IND	1.25	0.94	0.60	1.49	0.45	0.71	0.00	2.09	7.54
ZAF	0.73	1.03	2.19	2.97	2.33	1.15	2.01	0.00	12.41
TO	21.44	15.86	7.28	31.52	25.72	10.99	7.05	12.04	131.91
Inc.Own	21.44	15.86	7.28	31.52	25.72	10.99	7.05	12.04	TCI
NET	-0.14	-0.40	-0.55	1.90	0.26	-0.22	-0.48	-0.37	16.49
Spearman Correlations Connectedness									
	GRC	ISL	KOR	PRT	ESP	TUR	IND	ZAF	FROM
GRC	0.00	2.98	0.20	8.38	5.15	5.10	0.94	0.62	23.37
ISL	3.12	0.00	1.02	3.55	4.17	2.82	0.93	1.36	16.99
KOR	0.24	1.08	0.00	0.91	1.75	0.34	1.26	3.45	9.03
PRT	8.32	3.45	0.78	0.00	9.98	1.59	2.04	2.27	28.44
ESP	5.14	4.01	1.62	10.18	0.00	1.74	0.43	1.57	24.69
TUR	5.16	2.92	0.32	1.64	1.87	0.00	0.98	1.14	14.02
IND	1.10	0.99	1.28	2.28	0.51	1.00	0.00	1.38	8.55
ZAF	0.62	1.37	3.38	2.42	1.63	1.12	1.32	0.00	11.87
TO	23.70	16.81	8.61	29.36	25.07	13.72	7.90	11.78	136.95
Inc.Own	23.70	16.81	8.61	29.36	25.07	13.72	7.90	11.78	TCI
NET	0.33	-0.18	-0.42	0.92	0.38	-0.30	-0.65	-0.08	17.12
Kendall Correlations Connectedness									
	GRC	ISL	KOR	PRT	ESP	TUR	IND	ZAF	FROM
GRC	0.00	3.44	0.25	8.57	5.66	5.55	1.06	0.78	25.32
ISL	3.63	0.00	1.12	3.88	4.50	2.93	1.09	1.56	18.71
KOR	0.31	1.19	0.00	1.07	1.94	0.39	1.45	3.88	10.23
PRT	8.45	3.74	0.91	0.00	11.28	1.63	2.52	2.47	31.00
ESP	5.63	4.30	1.77	11.54	0.00	1.85	0.51	1.84	27.44
TUR	5.63	3.05	0.37	1.69	2.02	0.00	1.05	1.21	15.02
IND	1.25	1.17	1.49	2.85	0.63	1.07	0.00	1.66	10.11
ZAF	0.80	1.57	3.80	2.67	1.93	1.19	1.58	0.00	13.54
TO	25.70	18.47	9.70	32.27	27.97	14.62	9.26	13.40	151.38
Inc.Own	25.70	18.47	9.70	32.27	27.97	14.62	9.26	13.40	TCI
NET	0.38	-0.24	-0.54	1.26	0.53	-0.40	-0.85	-0.14	18.92

Table 5b: Model-based connectedness for low correlated returns

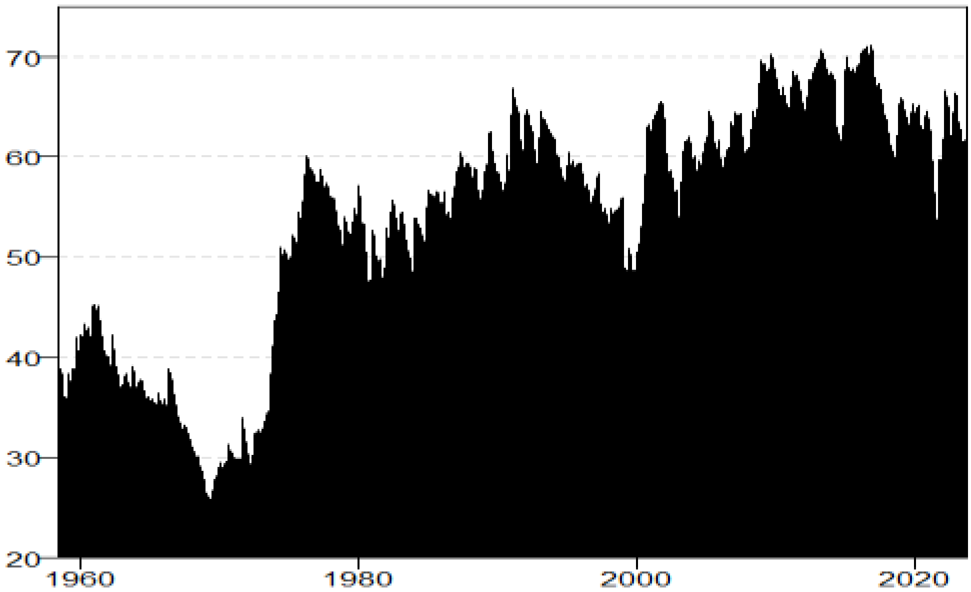
DY Connectedness									
	GRC	ISL	KOR	PRT	ESP	TUR	IND	ZAF	FROM
GRC	69.78	4.41	2.04	5.09	3.21	4.89	3.87	6.68	30.22
ISL	4.38	77.16	5.33	4.46	6.05	2.28	0.43	1.90	22.84
KOR	3.75	2.71	82.70	1.25	5.54	0.51	1.37	2.16	17.30
PRT	5.46	7.04	1.32	74.48	6.61	0.72	1.64	2.72	25.52
ESP	4.37	7.62	2.57	7.76	73.85	0.35	0.91	2.57	26.15
TUR	6.28	0.38	0.23	0.41	1.55	87.60	1.75	1.80	12.40
IND	3.14	0.68	2.00	1.46	1.49	0.79	87.93	2.50	12.07
ZAF	7.35	4.29	0.72	2.04	2.05	4.52	0.69	78.34	21.66
TO	34.74	27.14	14.22	22.48	2.50	12.07	10.68	20.33	168.15
Inc.Own	104.52	104.30	96.92	96.96	100.35	99.67	98.61	98.67	TCI
NET	4.52	4.52	-3.08	-3.04	0.35	-0.33	-1.39	-1.33	21.02

Time-Varying Parameter-VAR Connectedness									
	GRC	ISL	KOR	PRT	ESP	TUR	IND	ZAF	FROM
GRC	62.53	5.40	2.16	11.07	7.10	5.59	2.69	3.46	37.47
ISL	4.82	63.02	7.01	7.72	5.50	6.54	3.44	1.95	36.98
KOR	3.31	5.07	74.16	4.63	2.87	4.18	3.43	2.36	25.84
PRT	9.40	6.10	4.91	59.61	9.93	4.11	3.06	2.89	40.39
ESP	6.44	7.98	3.07	11.64	60.65	4.82	2.79	2.62	39.35
TUR	6.41	4.16	5.44	4.60	3.46	69.99	2.38	3.57	30.01
IND	3.12	3.21	2.26	3.08	2,79	1.83	81.89	2.61	18.91
ZAF	3.83	4.73	5.38	4.99	3.37	7.84	3.30	66.56	33.44
TO	37.33	36.64	30.24	47.73	35.01	34.90	21.09	19.44	262.38
Inc.Own	99.86	99.66	104.40	107.34	95.67	104.89	102.18	86.00	TCI
NET	-0.14	-0.34	4.40	7.34	-4.33	4.89	2.18	-14.00	32.80

Pearson, Spearman and Kendall



TVP-VAR



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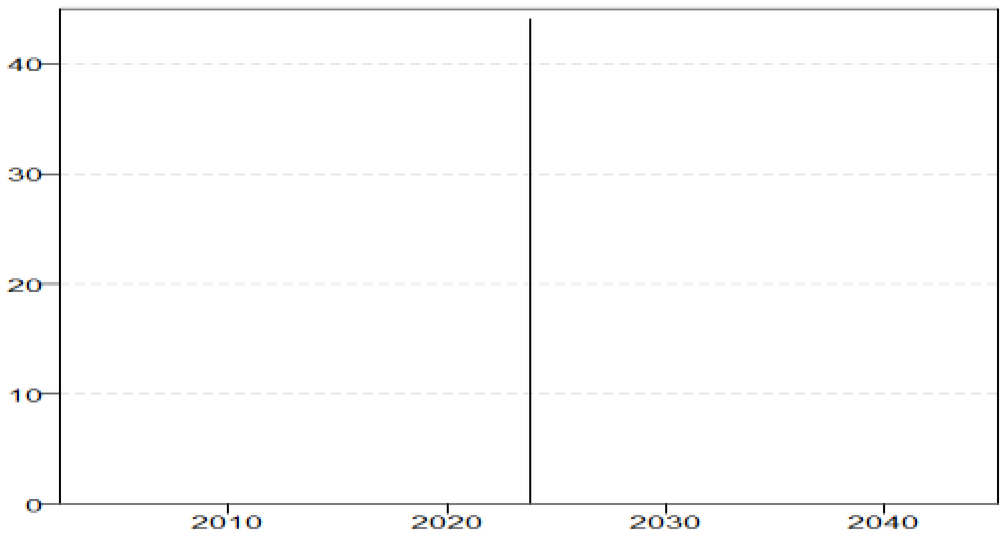
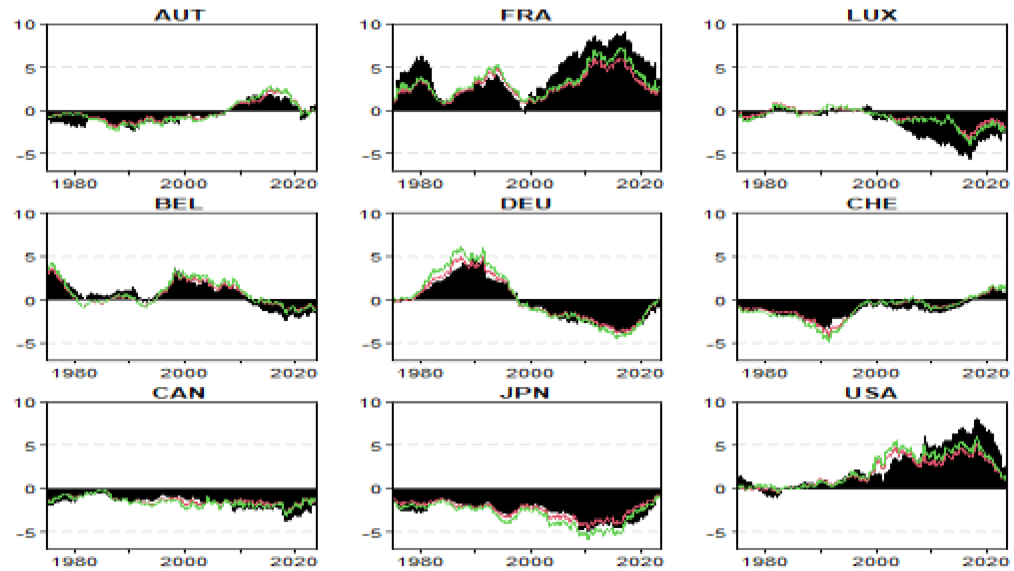
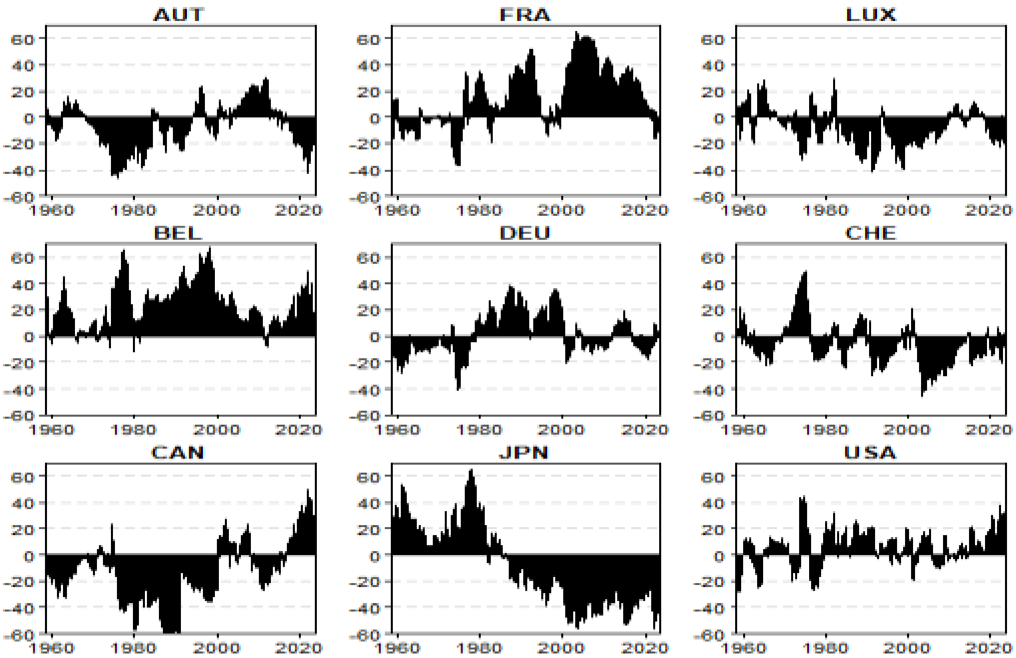


Figure 1: Dynamic total connectedness for high correlations (Pearson, Spearman, Kendal, TVP-VAR and DY)

Pearson, Spearman and Kendall



TVP-VAR



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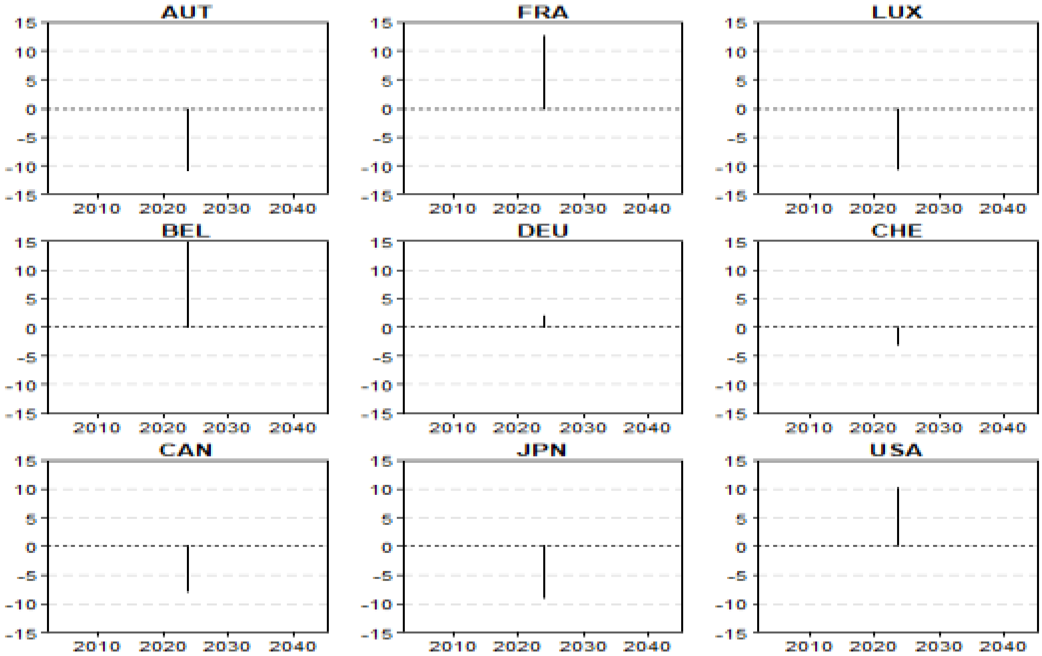
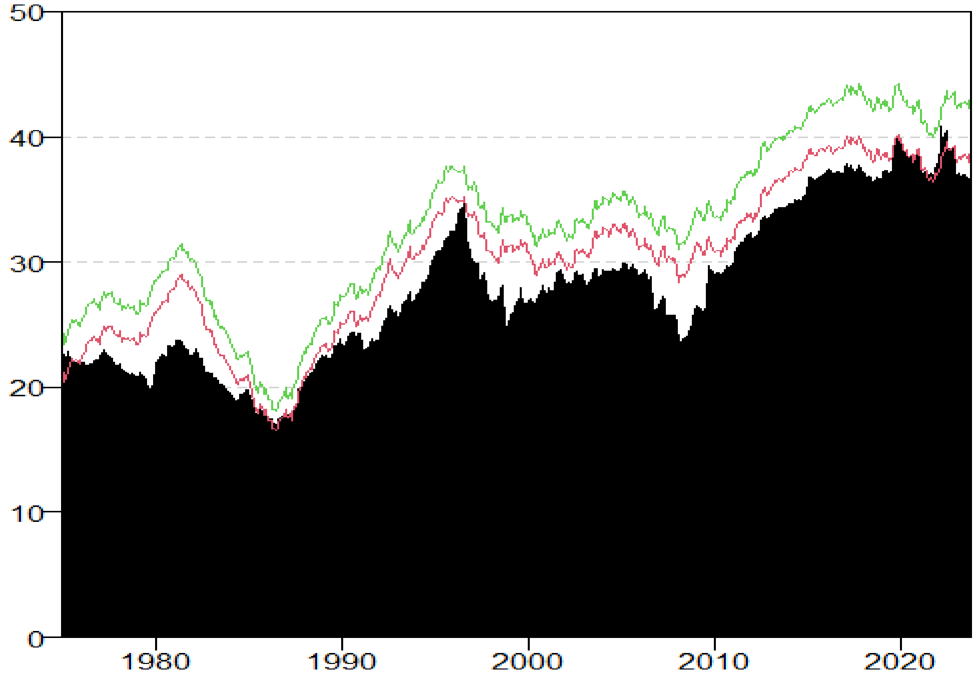
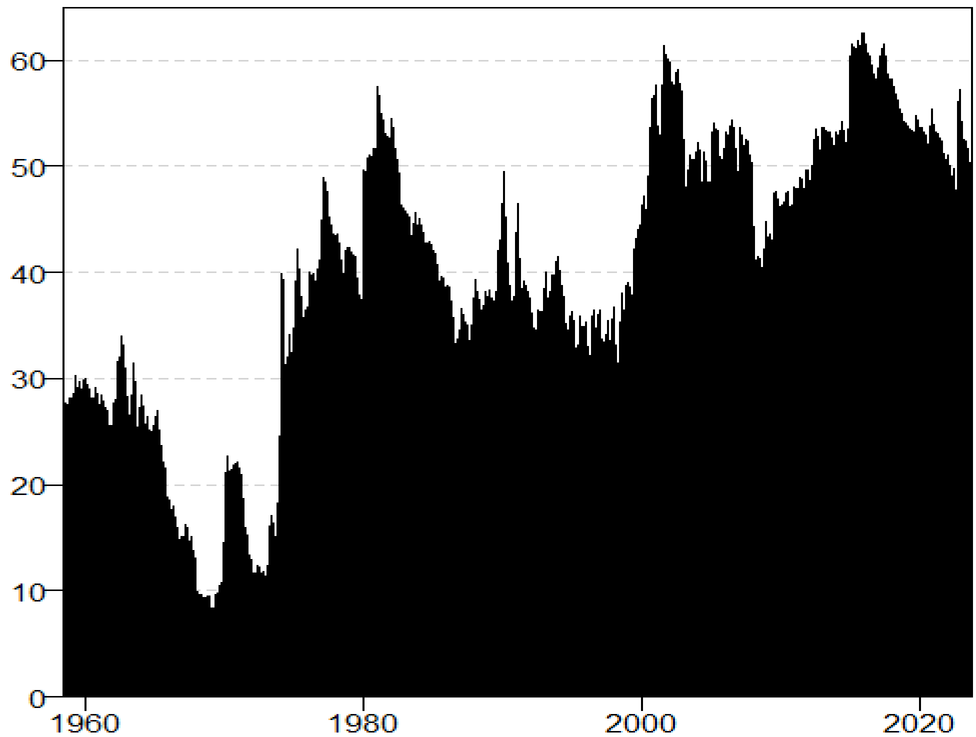


Figure 2: Net dynamic connectedness for high correlations (Pearson, Spearman, Kendal, TVP-VAR and DY)

Pearson, Spearman and Kendall



TVP-VAR



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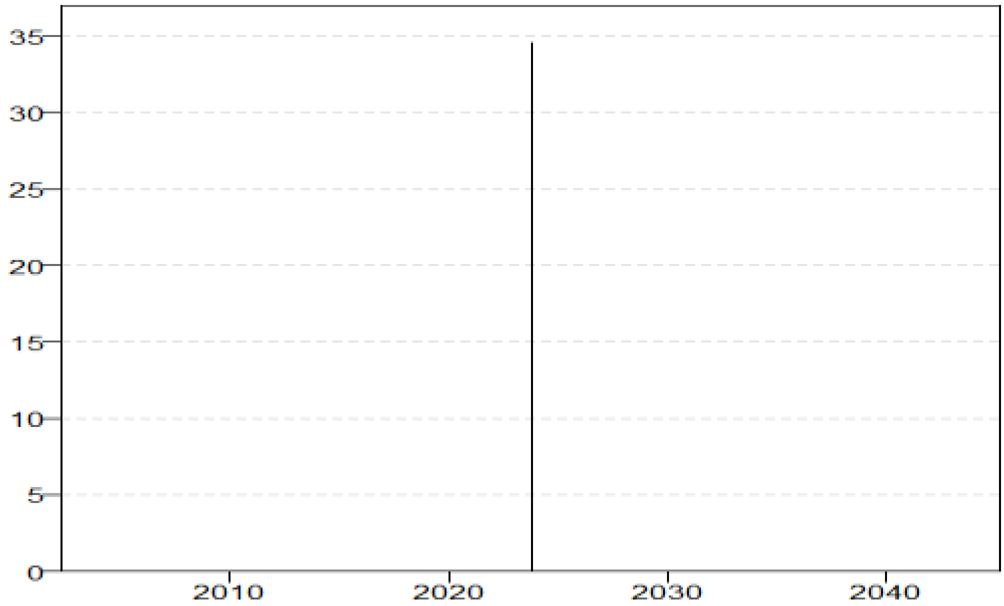
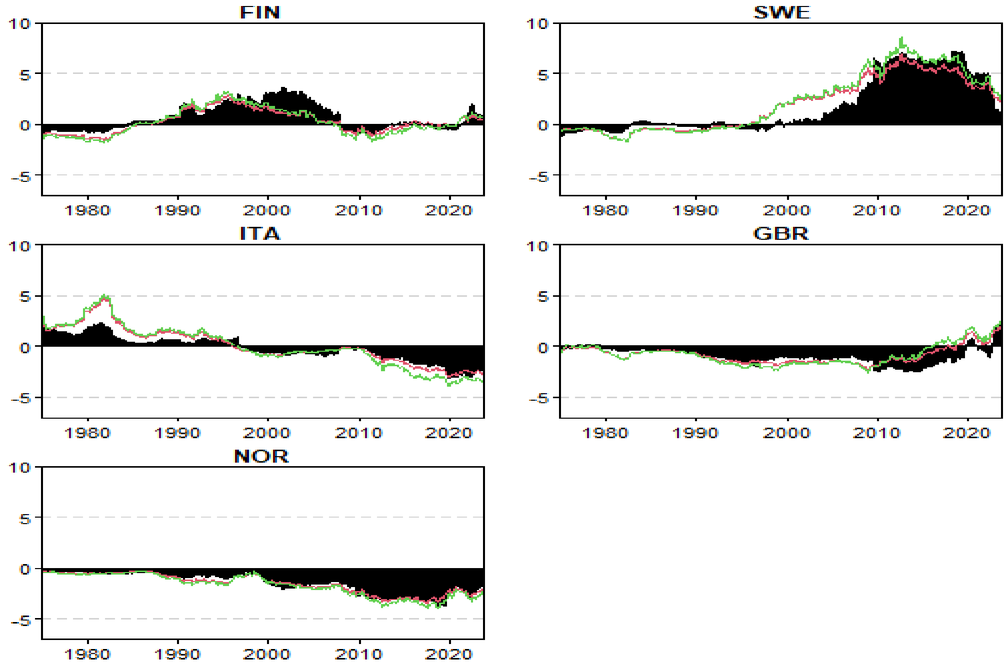
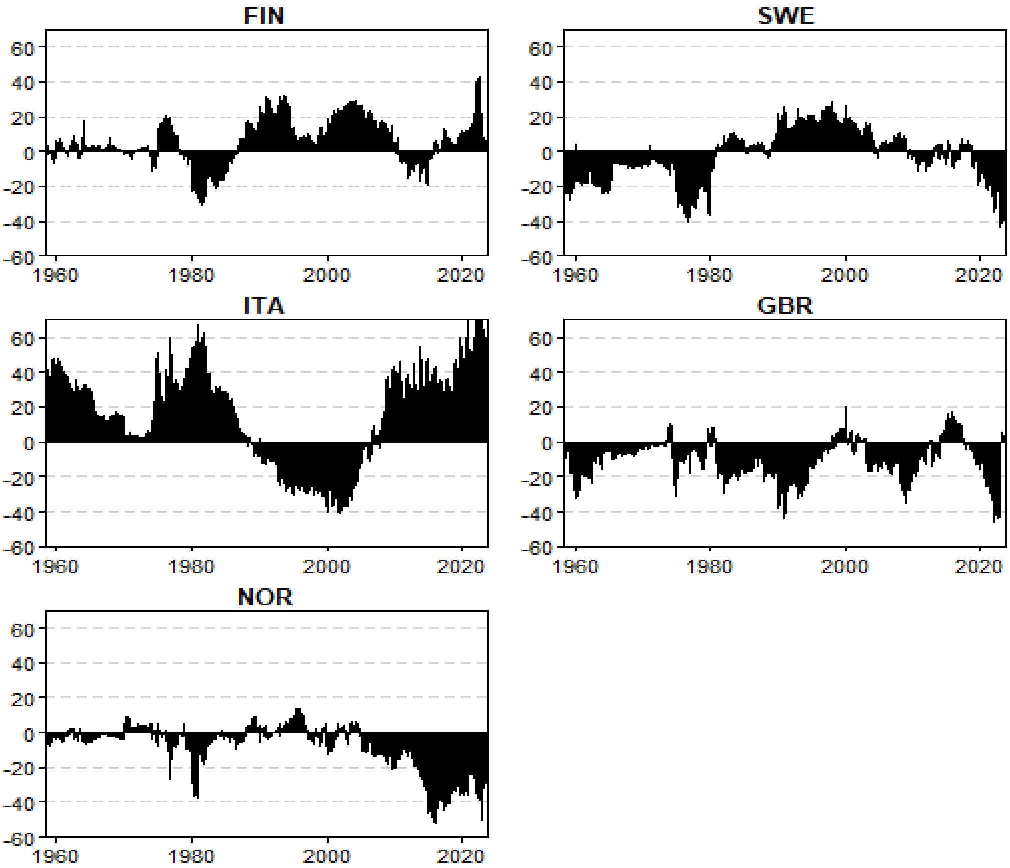


Figure 3: Dynamic total connectedness for medium correlations (Pearson, Spearman, Kendal, TVP-VAR and DY)

Pearson, Spearman and Kendall



TVP-VAR



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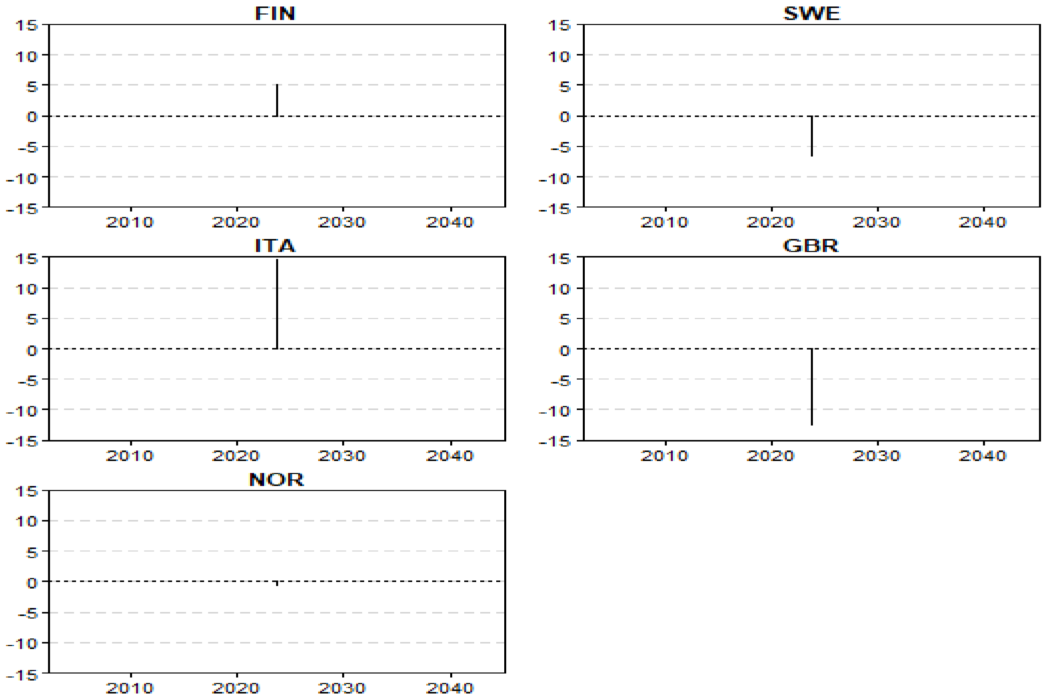
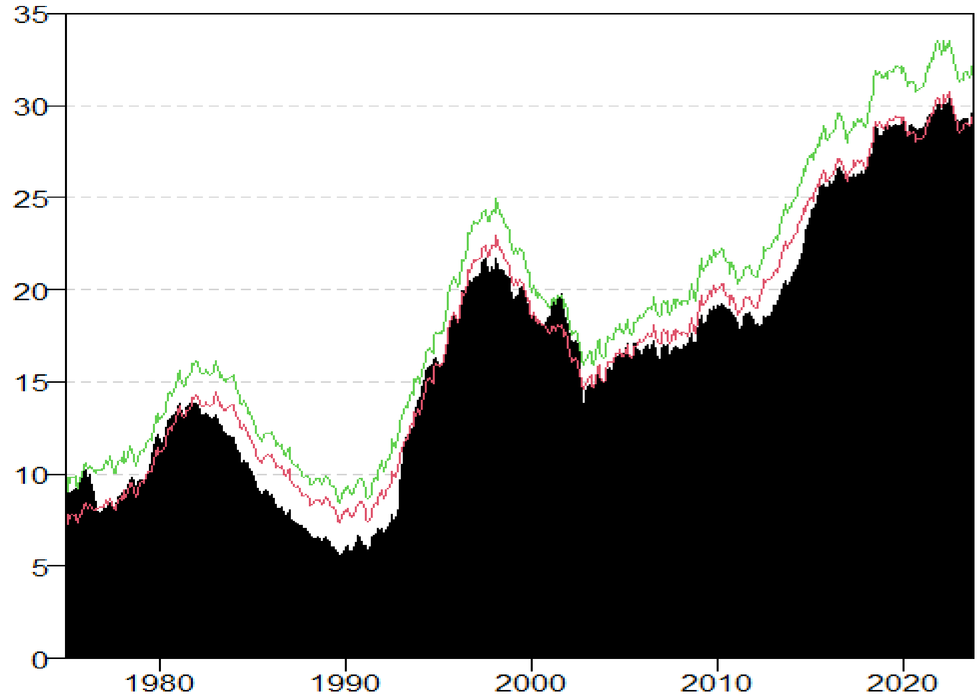
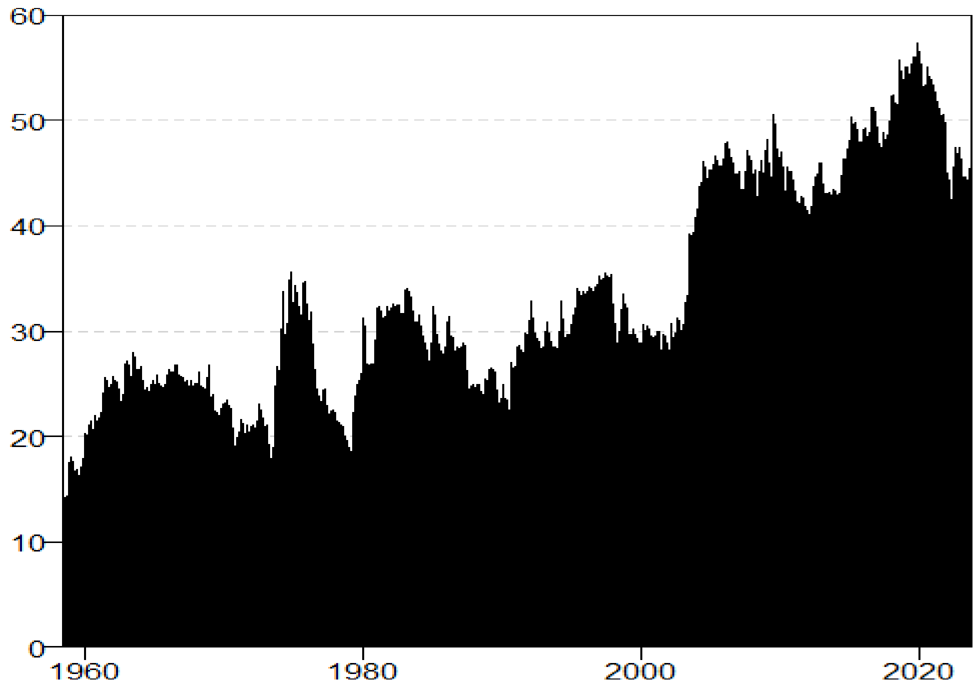


Figure 4: Net dynamic connectedness for medium correlations (Pearson, Spearman, Kendal, TVP-VAR and DY)

Pearson, Spearman and Kendall



TVP-VAR



DY

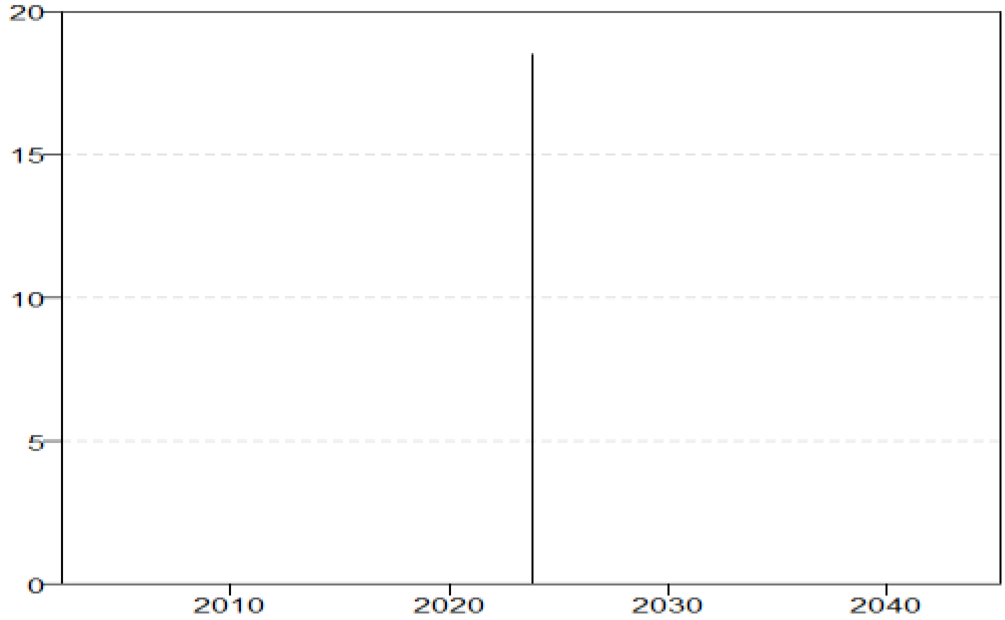
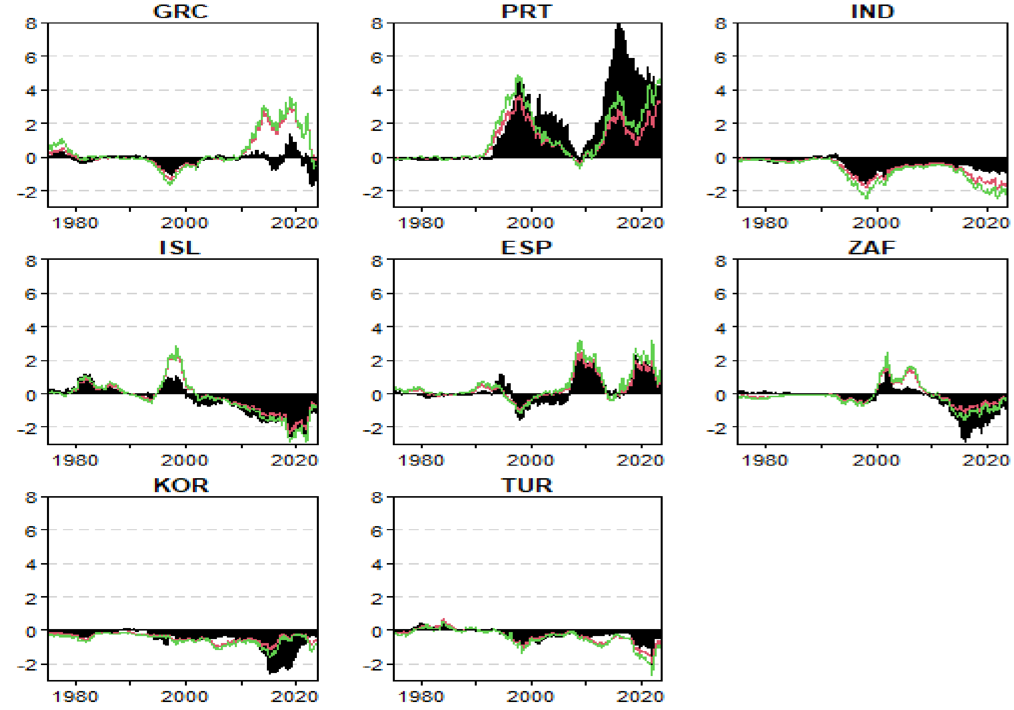
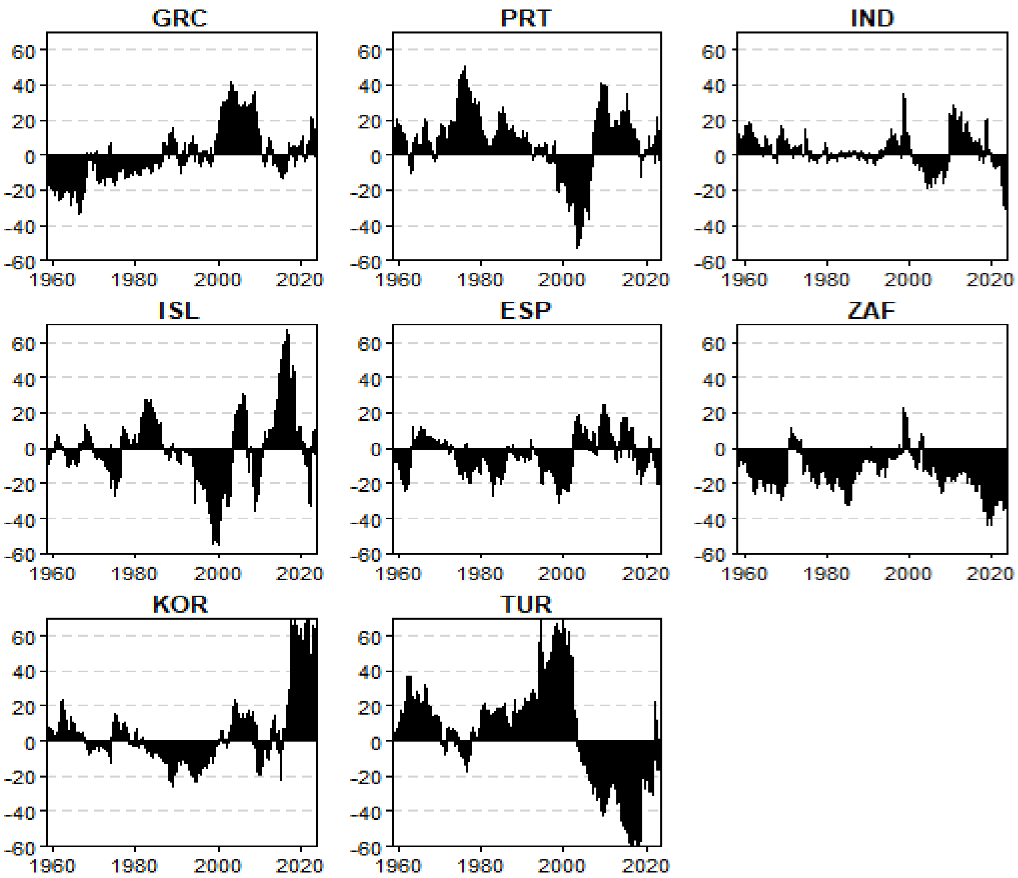


Figure 5: Dynamic total connectedness for low correlations (Pearson, Spearman, Kendal, TVP-VAR and DY)

Pearson, Spearman and Kendall



TVP-VAR



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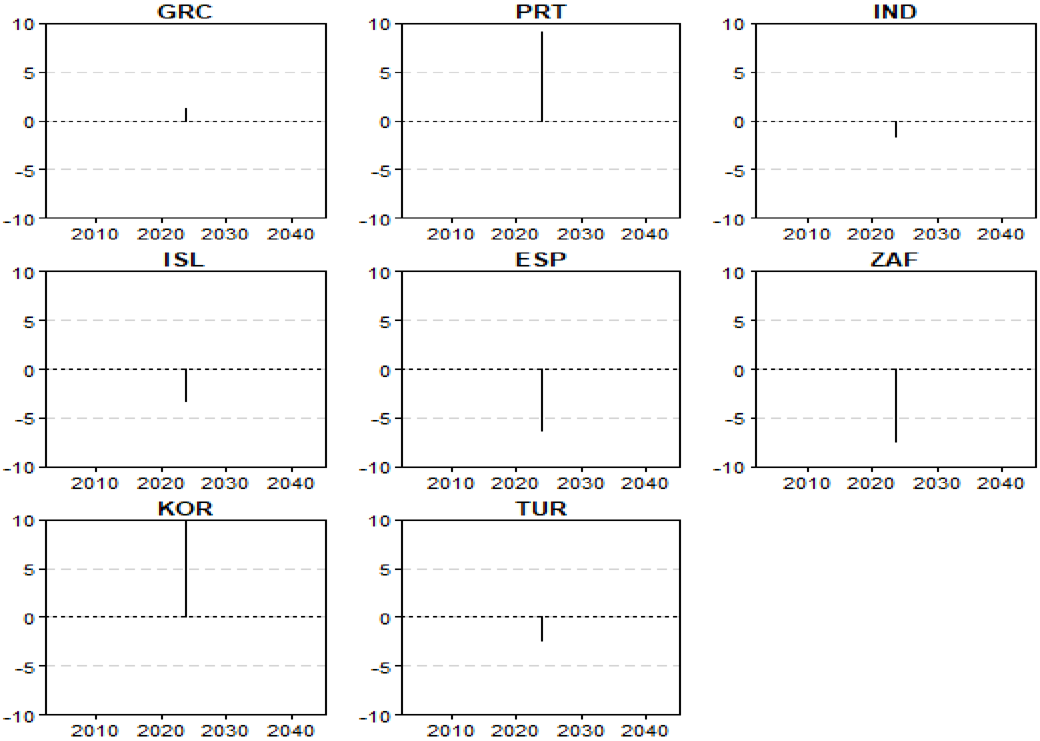

Figure 6: Net dynamic connectedness for low correlations (Pearson, Spearman, Kendal, TVP-VAR and DY)