Chapter 13

Market Linkages and Their Impact on G7 Economies: Exploring Network Connectedness

Erhan Uluceviz[1*]

Abstract

This project departs from the well-established finding in macrofinance literature that financial variables have a significant impact on macroeconomic variables. Building on this, we investigate the volatility connectedness among the stock markets of the Group of Seven (G7) countries, which account for a significant portion of global economic output and stock market capitalization. Using the Diebold-Yilmaz Connectedness Index (DYCI) framework, we analyze the connectedness of the G7 stock markets over the period from January 2010 to June 2024. We assess how volatility spills across these markets, particularly in response to major global events such as the 2011 U.S. credit rating downgrade, the 2013 "Taper Tantrum," the 2016 U.S. presidential election, and the COVID-19 pandemic. The findings reveal that market connectedness is highly dynamic, with the U.S. consistently acting as the primary connectedness source, followed by Germany and France during times of market stress. Japan, in contrast, is predominantly a net receiver of volatility. The results further highlight the varying roles of the G7 markets in volatility connectedness, indicating limited roles for the UK, Italy and Canada. The study also explores the relative importance of each market as a shock propagator, finding that the U.S. has the highest shock propagation capacity, while Japan consistently has the lowest. Consistent with the literature, our findings reveal a strong relationship between market volatility and the macroeconomic policy impacts of G7 economies, particularly during key market and economic episodes. These insights contribute to the understanding of economic and financial market interaction and provide valuable implications for policymakers and investors navigating the interconnected global markets.

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1. INTRODUCTION

Recent financial crises and the subsequent recessions, including the 2007-2009 Global Financial Crisis and the COVID-19 pandemic, have underscored the need to better understand the linkages between the financial sector and key macroeconomic variables, such as GDP and unemployment. These linkages have been explored using various approaches in both developing and developed countries. For example, Abildgren (2016) examines the interaction between financial shocks and business cycles in Denmark, the USA, and Canada over the past century. While Karanasos, Yfanti, and Hunter (2022) and Ngene (2021) focus on the effects of financial shocks on the U.S. economy, Joaqui-Barandica, Gomez Daza, and Lopez-Estrada (2024) and Biswas et al. (2024) investigate similar dynamics in emerging economies. Wang and Huang (2022) attempt to forecast the Chinese macroeconomy by analyzing the volatility connectedness of financial institutions. Given the understanding that financial shocks impact the real economy, we explore the volatility connectedness among the stock markets of the Group of Seven (G7) countries, offering valuable insights into the interactions of major global economies and their stock markets.

G7 is an informal forum comprising of seven advanced economies: the United States of America (U.S. or USA), Germany (GER), the United Kingdom (U.K.), France (FRA), Japan (JAP), Italy (ITA), and Canada (CAN). As of the end of 2023, G7 countries account for approximately 44% of global GDP (World Bank, n.d.; authors' calculations). An indicative value of their stock market capitalization represents approximately 60% of the global total as of 2022 (see Section 2).

G7 countries are highly integrated through political, regional, and trade channels, and they host the world's largest financial markets. These nations are also home to some of the most innovative firms that drive global trends in manufacturing and technology, and often feature cross-listed companies across their stock markets. Due to their strong economic ties and interdependence, it is well-known that the stock markets of G7 countries are closely linked, with fluctuations in these markets having significant implications for both developed and developing economies. The relationship between economic growth and financial integration has been extensively discussed, with Bekaert and Harvey (1995) arguing that the two are closely connected. Additionally, Tahai, Rutledge, and Karim (2004) find significant comovement in G7 stock market returns, suggesting a higher degree of market integration.

More recently, Attilio, Faria, and Prado (2024) examined the impact of the U.S. stock market on the BRICS (Brazil, Russia, India, China, and South Africa) and G7 economies. They found that greater financial integration amplifies the influence of the U.S. stock market on both the BRICS and G7. Furthermore, they observed that, compared to the BRICS countries, G7 stock markets and policy rates are more sensitive to shocks originating from the U.S. These studies collectively highlight the significant interconnectedness of G7 stock markets, which is central to understanding the dynamics we explore in this paper. In another study, Zhang, Sha, and Xu (2021) examined volatility spillovers between the G7 and BRIC countries. They found that key events, such as the European Debt Crisis, the China-US Trade War, and the Covid-19 Pandemic, significantly strengthened volatility spillovers in global financial markets. Ma, Wang, and He (2022) investigate the spillovers between economic policy uncertainty (EPU) and stock market realized volatility in G7 countries using the methods of Diebold and Yilmaz (2012) and Barunik and Krehlik (2018). They find that the strongest spillovers from EPU to stock market volatility occur within a 3–18 month period, indicating that policy uncertainty has a gradual impact on market risk over time. This suggests that, when making investment decisions, investors should focus not only on recent economic policies but also on macroeconomic conditions from the past 18 months.

Building on the existing literature, this paper aims to investigate volatility connectedness among the G7 stock markets and analyze how these dynamics have evolved over time. Additionally, we assess the relative importance of each market as a shock propagator. Our approach is based on a well-established and widely used methodology, specifically the Diebold-Yilmaz Connectedness Index (DYCI), introduced in a series of papers by Diebold and Yilmaz (2009, 2012, 2014). Furthermore, we incorporate an extension of the DYCI methodology developed by Schmidbauer, Roesch, and Uluceviz (2013, 2017), and Schmidbauer, Roesch, Uluceviz, and Erkol (2016). Schmidbauer et al. (2013, 2017; 2016) introduce a centrality measure, derived from the DYCI framework, to quantify the relative importance of each G7 market as a shock propagator. For additional insights into centrality measures within the network literature, see Newman (2010).

The close relationship between the real and financial sectors of selected developed economies, including Switzerland and the U.S., has been studied within the connectedness index framework by Uluceviz and Yilmaz (2020, 2021). Their findings suggest that when the real side of the economy is represented solely by real variables, it acts as a net receiver of connectedness from the financial variables including the stock markets. Therefore, representing the G7 countries with their major stock indices indirectly allows us to explore the interactions between the economies of these nations as well.

Our analysis reveals that market connectedness is highly dynamic, responding to major global events such as the 2011 U.S. credit rating downgrade, the 2013 "Taper Tantrum," Donald Trump's 2016 election, and the COVID-19 pandemic. The U.S. emerged as the primary source of volatility spillovers, while Europe, particularly Germany and France, played significant roles during crises. In contrast, Japan was predominantly a net receiver of volatility. Italy's contribution was limited, with no substantial role in transmitting or receiving shocks compared to other G7 countries. Canada and the U.K., had a relatively minor impact on overall volatility connectedness among the G7 markets. The findings also highlight the varying roles of the G7 countries as shock propagators. The U.S. consistently emerges as the most significant shock propagator, followed by Germany and France, which also play substantial roles. The U.K. and Italy contribute moderately to shock transmission, while Canada has a relatively smaller impact. Japan, despite its economic stature, is found to be the least significant shock propagator throughout the analysis period.

Our findings demonstrate a strong association between market volatility and the macroeconomic policy impacts of G7 economies, especially during critical market and economic events.

Our main contribution in this study, from both policy and investment perspectives, is to provide a clearer understanding of the interrelations among major developed economies and their stock markets through an approach that is both easy to interpret and apply.

The remainder of the chapter is organized as follows: Section 2 provides an overview of the data used in the analysis. Section 3 outlines the methodological approach. Section 4 presents the empirical findings, while Section 5 concludes with a summary and final remarks.

2. DATA

This paper examines the stock markets of the G7 countries, using the major indices to represent each market. The data were obtained from Yahoo Finance through its free-tier access.[2] We downloaded daily Open, High, Low, and Close (OHLC) data using the quantmod package (Ryan & Ulrich,

2 https://finance.yahoo.com. Yahoo Finance is part of the Yahoo network and offers a range of financial data, news, commentary, and personalized financial management services.

2024) in R (R Core Team, 2024). The sample period spans from January 5, 2010, to June 28, 2024, covering a total of 3,770 trading days.

Detailed information about the selected indices, their corresponding Yahoo Finance tickers, and the total market capitalizations for each market are provided in Table 1. It is important to note that the total market capitalization values for the respective countries are sourced from the World Bank, and the most recent data for each country may vary. Therefore, these values should be interpreted with caution. To provide an indicative value for the share of G7 stock markets in the global economy, we also include the total world market capitalization. We find that the G7 countries account for approximately 60% of the global market capitalization.

Given the downloaded OHLC data, we compute daily volatilities using the Garman and Klass (1980) approach, as applied in Diebold and Yilmaz (2009). We then compute the natural logarithm of each volatility series before proceeding with the estimation procedure outlined in Section 3. It is well documented that volatilities are serially correlated and skewed (Bates, 1991; Cont, 2001; Bollerslev, Gibson, & Zhou, 2011). Taking the logarithm helps approximate the volatility series to normality (Diebold & Yilmaz, 2014).

Table 1: Selected G7 Markets

Country	Index	Ticker	Market cap (USD mn)	Data Year
USA	S&P 500	^GSPC	40,297,980	2022
Germany	DAX	^GDAXI	1,889,664	2022
UK	FTSE 100	^FTSE	3,095,983	2022
France	CAC 40	^FCHI	2,365,950	2018
Japan	Nikkei 225	^N225	5,380,475	2022
Italy	FTSE MIB	FTSEMIB.MI	587,312	2014
Canada	S&P/TSX Composite	^GSPTSE	2,744,720	2022
G7 (total)			56,362,086*	
World			93,960,000	2022
G7/World			60%	

****: This sum is indicative due to the differences in the data years.***

Source: Worldbank, Market capitalization of listed domestic companies (current USD) and author's calculations. https://data.worldbank.org/indicator/CM.MKT.LCAP.CD.

3. DIEBOLD-YILMAZ CONNECTEDNESS INDEX APPROACH

In this section, we provide a brief introduction to the DYCI methodology, originally developed by Diebold and Yilmaz (2009, 2012, 2014), along with one of its extensions, as applied in this paper, by Schmidbauer et al. (2013, 2017; 2016). For a more detailed overview, interested readers are encouraged to refer to the original papers.

A covariance-stationary N-variable $VAR(p)$ model is given by:

$$x_t = \sum_{i=1}^{p} \varnothing_i x_{t-i} + \varepsilon_t,\ \varepsilon_t \sim iid(0, \Sigma),$$

which has a moving average (MA) representation of the form:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i},$$

where the $N \times N$ coefficient matrices A_i are determined by the recursive formula:

$$A_i = \varnothing_1 A_{i-1} + \varnothing_2 A_{i-2} + \cdots + \varnothing_p A_{i-p},\ A_0 = I_n,\ A_i = 0 \text{ for } i < 0.$$

These coefficient matrices govern the model dynamics. Our focus is on the variance decompositions, which estimate the proportion of the h-step ahead forecast error variance for x_i that is attributable to shocks to x_j, $\forall i \neq j$, for each i. The calculation of variance decompositions requires orthogonal innovations, typically achieved through identification schemes like Cholesky decomposition. However, this approach results in variable-ordering dependent outcomes. To address this issue, Diebold and Yılmaz (2012) use the generalized VAR approach, developed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), which accounts for correlated shocks and produces ordering-invariant results.

Pesaran and Shin (1998) demonstrate that, under the assumption of a multivariate normal distribution for the error term, ε_t, the h-step generalized impulse response function, scaled by the variance of the variable, represents node j's contribution to node i's h-step ahead generalized forecast error variance, denoted $\theta_{ij}^{g}(h)$ for $h = 1, 2, \ldots$, as follows:

$$\theta_{ij}^{g}(h) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{h-1} \left(e_i^{'} A_k \Sigma e_j\right)^2}{\sum_{k=0}^{H-1} \left(e_i^{'} A_k \Sigma A_k^{'} e_i\right)^2} \tag{1}$$

where Σ is the variance-covariance matrix of the error vector ε, σ_{jj} is the standard deviation of the error term in the jth equation, and e_j is the selection vector with a 1 in the jth position and zeros elsewhere. By normalizing each element of the variance decomposition matrix by the respective row sum, we obtain:

$$C_{i\leftarrow j}^{h} = \frac{\theta_{ij}^{g}\left(h\right)}{\sum_{j=1}^{N}\theta_{ij}^{g}\left(h\right)} \tag{2}$$

$C_{i\leftarrow j}^{h}$ is referred to as pairwise directional connectedness. In network theory, it is interpreted as the adjacency matrix of a weighted directed network, denoted by C, where the ij th element is c_{ij}.

The normalized entries of the generalized variance decomposition matrix in Equation 2 are used to construct a summary measure of the connectedness matrix C. Diebold and Yilmaz (2012) define the total connectedness index as:

$$C^{h} = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} C_{i\leftarrow j}^{h}}{\sum_{i,j=1}^{N} C_{i\leftarrow j}^{h}} = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} C_{i\leftarrow j}^{h}}{N} \tag{3}$$

The direct connectedness from node i (to node i) is given by the column (row) sums in C, excluding the node's connectedness to itself:

$$\text{from node } i \text{ to others}: C_{\bullet\leftarrow i} = \sum_{k=1,\, i\neq k}^{N} c_{ki} \tag{4}$$

$$\text{to node } i \text{ from others}: C_{i\leftarrow \bullet} = \sum_{k=1,\, k\neq i}^{N} c_{ik} \tag{5}$$

The difference between shocks originating from and directed to node i provides a measure of the net directional connectedness transmitted from node i to all other nodes. This is referred to as:

$$C_{i} = C_{\bullet\leftarrow i} - C_{\mathrm{i}\leftarrow \bullet} \tag{6}$$

To extend the DYCI framework, Schmidbauer et al. (2013, 2017; 2016) assume that all available information about the network throughout day t is contained in C. Additionally, if an initial hypothetical shock of unit size hits node k on day t, it will propagate across the nodes of the network throughout day t as follows:

$$n_{s+1} = C.n_{s}\ ,\ s = 0, 1, 2, \ldots \tag{7}$$

A hypothetical shock is denoted as $n_0 = (0,\ldots,0,1,0,\ldots,0)$, where 1 is the k th element of n_0 (with step $s = 0$ representing the initial shock). By iterating Eq. (7) and examining the steady-state properties of the model as $s \to \infty$, we obtain:

$$\mathbf{v}' = \mathbf{v}'.C \tag{8}$$

When the left eigenvector $\mathbf{v} = (v_1,\ldots,v_N)'$ of C is normalized so that $\sum_{k=1}^{N} v_k = 1$, v_k is referred to as the propagation of node k. Intuitively, v_k represents the power of node k as a volatility transmitter within the network. A closely related concept in social network analysis, eigenvector centrality, is also widely used, as discussed in Bonacich (1987).

Empirically, we fit a standard VAR(3) model to $N = 7$ endogenous variables, representing the volatility of major stock market indices from the G7 countries. We use rolling data windows of size 250 (i.e., the sample for day t includes data from days $t-249$ to t). Following Diebold and Yilmaz (2012), we apply the ordering-invariant impulse response function identification approach proposed by Pesaran and Shin (1998). Forecasting $h = 20$ steps ahead, we compute the forecast error variance decomposition. This procedure is repeated for each t, generating a sequence of connectedness matrices.

4. EMPIRICAL RESULTS

This section presents the empirical results of our estimations based on the DYCI approach outlined in Section 3. We focus exclusively on the dynamic results, as they are more pertinent to our analysis. These results offer an overview of key events from 2010 to 2024 that contributed to unprecedented structural changes in the global economy, including the COVID-19 pandemic.

Since the DYCI approach relies on rolling windows of VAR estimations, selecting the appropriate lag length is a crucial first step in any connectedness analysis. To determine a suitable lag length, we performed estimations for lag lengths ranging from 1 to 5 using a 250-day rolling window. A 250-day window is commonly used in daily analysis, as it roughly corresponds to one year of trading days (around 252 days). Additionally, since the DYCI methodology involves the decomposition of forecast error variance, it is important to choose a forecast horizon that allows for stabilization of the forecast error variance decomposition. Shorter forecast horizons often fail to achieve this stabilization; however when we selected h = 20 days, our results were sufficiently stable. Given these choices, we plot the connectedness index results and select the appropriate lag length based on the most suitable outcome. Figure 6 displays the total connectedness results, including the maximum and minimum index values for each day within the shaded region, corresponding to VAR lag lengths ranging from 1 to 5. The VAR(3) model results are plotted as a dark line. We observe that the VAR(3) model fits well and is sufficiently parsimonious, leading us to select a lag length of 3.

Proceeding with the selected model, we first plot the connectedness index series in Figure 1 which is estimated using Equation 3. The index starts at 64.20% on December 20, 2010 and ends at 45.37% on June 28, 2024. It fluctuates between a minimum of 37.83% on December 14, 2017 and a maximum of 76.16% on June 15, 2020. The dynamics of the index are more relevant than the index values, and we briefly discuss key episodes observed during the analysis period.

The index value at the beginning of the analysis period represents the highest point throughout the entire period, excluding the COVID-19 pandemic. After this, the index begins to decrease throughout 2011, until it experiences a sharp increase at the beginning of August 2011, following the S&P downgrade of the U.S. credit rating from AAA to AA+ on August 5, 2011.[3] It oscillates above 60% until June 2012. The index starts decreasing, and further fueled, by the annoucement of a third round of Quantitative Easing (QE3) by Federal Reserve (Fed).[4] The decrease in the index lasted until, end of May 2013, the time Fed Chairman Bernanke testified before the U.S. Congress' Joint Economic Committee, where he revealed the Federal Open Market Committee's (FOMC) intention to taper bond purchases. His testimony triggered a rise in bond yields and a decline in global stock prices, an event known as the "Taper Tantrum."[5] Increase of the index lasted until early November 2016 when Donald Trump was elected the President of the U.S. Expectations of fiscal stimulus and tax cuts under a Republican-controlled Congress led to a surge in equity markets.[6] By the end of 2017, the index had reached an all-time low. It then rose until February 2018,

3 https://www.nytimes.com/2011/08/06/business/us-debt-downgraded-by-sp.html. Accessed November 25, 2024.

4 https://money.cnn.com/2012/09/13/news/economy/federal-reserve-qe3/index.html. Accessed November 25, 2024.

5 https://www.reuters.com/article/us-usa-fed-2013-timeline-idUSKCN1P52A8. Accessed on November 25, 2024.

6 https://www.ft.com/content/6d24125c-c066-11e6-9bca-2b93a6856354. Accessed November 25, 2024.

fluctuating within the 50%-56% range, until the end of 2019. During the onset of the COVID-19 pandemic[7], the index peaked at 76.02% on March 16, 2024, just below its all-time high of 76.16%, which occurred on June 16, 2024. The index remained above 70% until December 2020, before falling to the high 50% range, likely due to significant gains in the U.S. stock markets. The year 2020 ended with the Dow rising by 7.2%, the S&P 500 gaining 16.3%, and the Nasdaq surging 43.6%.[8] The index fluctuated around, and often exceeded, 60% until the end of May 2023, after which it began to decline through the remainder of the analysis period. This decline coincided with the end of the COVID-19 pandemic, as the World Health Organization (WHO) declared on May 5, 2023, the cessation of COVID-19 as a public health emergency, while stressing that the disease remains a global threat.[9]

Figure 2 consists of sub-figures of size 8 × 8, summarizing the time series of the total and directional dynamic connectedness indices. This figure contains the time series of all the connectedness matrices that form the basis of the analysis. The time series of the 7 × 7 sub-figures created by the first 7 rows and 7 columns in Figure 2 correspond to Equation 1. The connectedness index calculated using Equation 3 is also shown in the bottom-right corner of this figure. The last row ("to others") in Figure 2, excluding the right-most plot, corresponds to Equation 4, while the last column ("from others"), excluding the bottom plot, corresponds to Equation 5. We focus diagonal sub-figures of the first 7 × 7 sub-figures. These plots represent the own shares of connectedness, i.e., the connectedness arising from and directed towards itself. A higher level of own connectedness indicates a lower impact of these markets on others. Japan appears to have the highest own share of connectedness throughout the analysis period, suggesting that it acts as a lower volatility connectedness source with the rest of the G7 markets. It ranks first with an average own connectedness value of 63.79%, while France ranks last with an average value of 31.36%.

To assess the connectedness to (from) markets, we focus on the "to others" ("from others") columns in Figure 1 and present a concise version of these in Figure 3. Additionally, we compute and plot the net effect using Equation 6. The results indicate that, on average, the U.S. is the largest net source of volatility connectedness towards the other G7 markets. With

7 https://time.com/5791661/who-coronavirus-pandemic-declaration/. Accessed November 25, 2024.

8 https://www.npr.org/2020/12/31/952267894/stocks-2020-a-stunning-crash-then-a-record-setting-boom-created-centibillionaire. Accessed November 25, 2024.

9 https://news.un.org/en/story/2023/05/1136367. Accessed 2024-11-25.

a net connectedness of 13.10%, the U.S. contributes significant volatility connectedness to the rest of the G7. In contrast, Japan is the market that receives the most connectedness from others, with an average net connectedness of -21.15%. The U.S. was also a major source of connectedness during the end of May and early June 2019, with net connectedness from the U.S. to other markets peaking at 66.81% on June 6, 2019. This surge is likely linked to the large sell-offs in May 2019 and U.S. President Trump's tweets about escalating trade tensions between the U.S. and China, as well as concerns about global economic growth.[10] Continental European countries—Germany, France, and Italy—also experienced significant spikes in connectedness to other markets following the onset of the Russia-Ukraine war in late February 2022. They acted as net sources of connectedness, with average values of 3.85%, 6.70%, and 0.63%, respectively. In contrast, the UK was a net receiver, with a connectedness value of -5.59%. Meanwhile, Canada functioned as a net source, contributing a connectedness value of 2.47%.

To analyze the net connectedness from the major net connectedness source, the U.S., we present Figure 4, which illustrates the net directional connectedness from the U.S. to the respective G7 stock markets. Excluding the COVID-19 and the mid-2013 "Taper Tantrum" periods, the U.S. predominantly acts mostly as a net source of connectedness. Referring back to our earlier discussion of Japan in Figure 2, where we noted that Japan mostly transmits connectedness to itself rather than to others, we observe that the U.S. plays a significant role in transmitting connectedness to Japan. The U.S. is almost always a net source to Japan, with only a few brief exceptions. European markets typically act as receivers of connectedness, except during the COVID-19 period, when they function as net sources of connectedness towards the U.S.

To quantify the relative importance of each market as a shock propagator, we present Figure 5, which displays the propagation values estimated using Equation 8. These values sum to 1, and the larger the value for a country, the more significant its market as a shock propagator. Interestingly, despite Japan being one of the wealthiest countries in the G7, it has the lowest importance as a shock propagator throughout most of the analysis period. Schmidbauer et al. (2013) demonstrated that propagation values can be interpreted as probabilities, representing the stationary distribution of a Markov chain derived from a suitable transformation of the connectedness

10 https://www.cnbc.com/2019/05/31/the-markets-drop-in-may-felt-serious-but-it-is-normal-for-stocks.html. Accessed 2024-11-27.

matrix C. As a result, the sum of the propagation values provides a valid measure. When grouping countries by continent, the relative importance of markets becomes even more apparent, likely due to the influence of trade channels on market importance. Averaging the propagation values over time, we find that the U.S. has the largest propagation value at 0.18, followed by Germany (0.16), the UK (0.14), France (0.16), and Italy (0.15). Canada has a propagation value of 0.15, while Japan has the smallest at 0.07. When grouped by continent, Europe (Germany, France, Italy, and the UK) has a combined propagation value of 0.60, the Americas (U.S. and Canada) have 0.33, and Asia (Japan) has 0.07. Averaging over different periods yields similar results. However, when we focus on the period from the beginning of the analysis until the end of May 2013, European propagation value rises to 0.66, while the American value is 0.29, and Japan's value drops to 0.05. This shift is likely attributable to the European sovereign debt crisis during the 2009-2012 period post global financial crisis.

5. SUMMARY AND CONCLUSIONS

This paper examines the stock markets of the G7 countries (the U.S., Germany, France, the U.K., Japan, Italy, and Canada) from 2010 to 2024, using their major indices as proxies for each market. The analysis focuses on daily volatility connectedness, employing the Diebold-Yilmaz Connectedness Index methodology (Diebold and Yilmaz, 2009, 2012, 2014), which applies rolling Vector Auto Regressive models to estimate volatility connectedness. Additionally, the study incorporates an extension by Schmidbauer et al. (2013, 2017; 2016) to assess the relative importance of each G7 market as a shock propagator.

The goal is to uncover patterns of financial connectedness and identify significant global events that led to structural shifts in the connectedness behavior of these stock markets.

The study reveals that volatility connectedness among the G7 markets is highly dynamic and fluctuates significantly in response to major global events, including the U.S. credit rating downgrade in 2011, the Federal Reserve's announcement of the prospective "Taper Tantrum" in May 2013, the election of Donald Trump as U.S. president in 2016, and the global disruption caused by the COVID-19 pandemic in 2020. These events are marked by substantial fluctuations in the total connectedness index, with notable peaks and following troughs.

The U.S. consistently emerged as the primary source of volatility spillovers, playing a central role in shaping connectedness across the G7 markets, particularly during geopolitical crises such as the U.S.-China trade tensions in 2019 and the COVID-19 pandemic from from early 2020 to mid-2023. In contrast, Japan, despite being one of the wealthiest G7 nations, played a more passive role in volatility connectedness, often serving as a net receiver from other markets, particularly during periods of market stress.

The study also highlights the significant role of European countries, particularly Germany and France, in contributing to market connectedness during key events such as the European sovereign debt crisis (2009-2012), the Russia-Ukraine war that began in late February 2022, and the COVID-19 pandemic from early 2020 to mid-2023. These countries became major sources of increased volatility connectedness, reflecting the substantial impact of regional economic and policy uncertainties on global marketsIn contrast, markets like the UK were primarily net receivers of volatility connectedness, with relatively smaller contributions. Italy and Canada, on the other hand, had a minimal impact on overall connectedness among the G7 countries.

The results suggest that global economic shocks, such as the COVID-19 pandemic, had a profound impact on market connectedness, significantly raising the levels of connectedness among the G7 markets. The study concludes that the U.S. stock market is the most influential driver of global volatility connectedness and shock propagator, with European countries following the U.S. in terms of their impact. In contrast, Japan remains less influential both as a source of volatility connectedness and as an important shock propagator.

Overall, the paper provides valuable insights into the dynamics of G7 market connectedness, highlighting the shifting roles of different G7 markets in responding to and transmitting global economic shocks. These findings underscore the importance of understanding market dynamics for policymakers and investors as they navigate an increasingly interconnected global financial system. Future research could explore subgroups within the G7, incorporate their trade relations, and apply alternative volatility measures to gain a deeper understanding of the various dimensions of G7 connectedness.

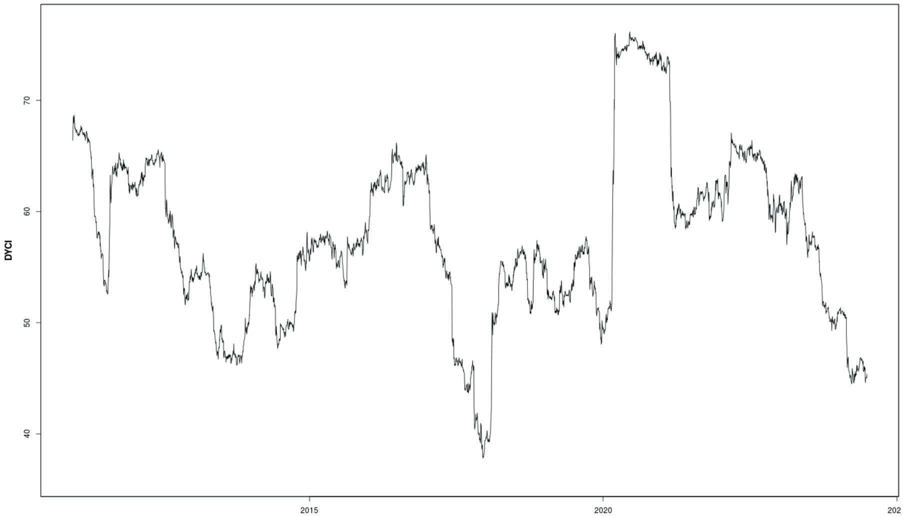

Fig. 1 Total connectedness index

Fig. 2 Total and pairwise dynamic connectedness indices

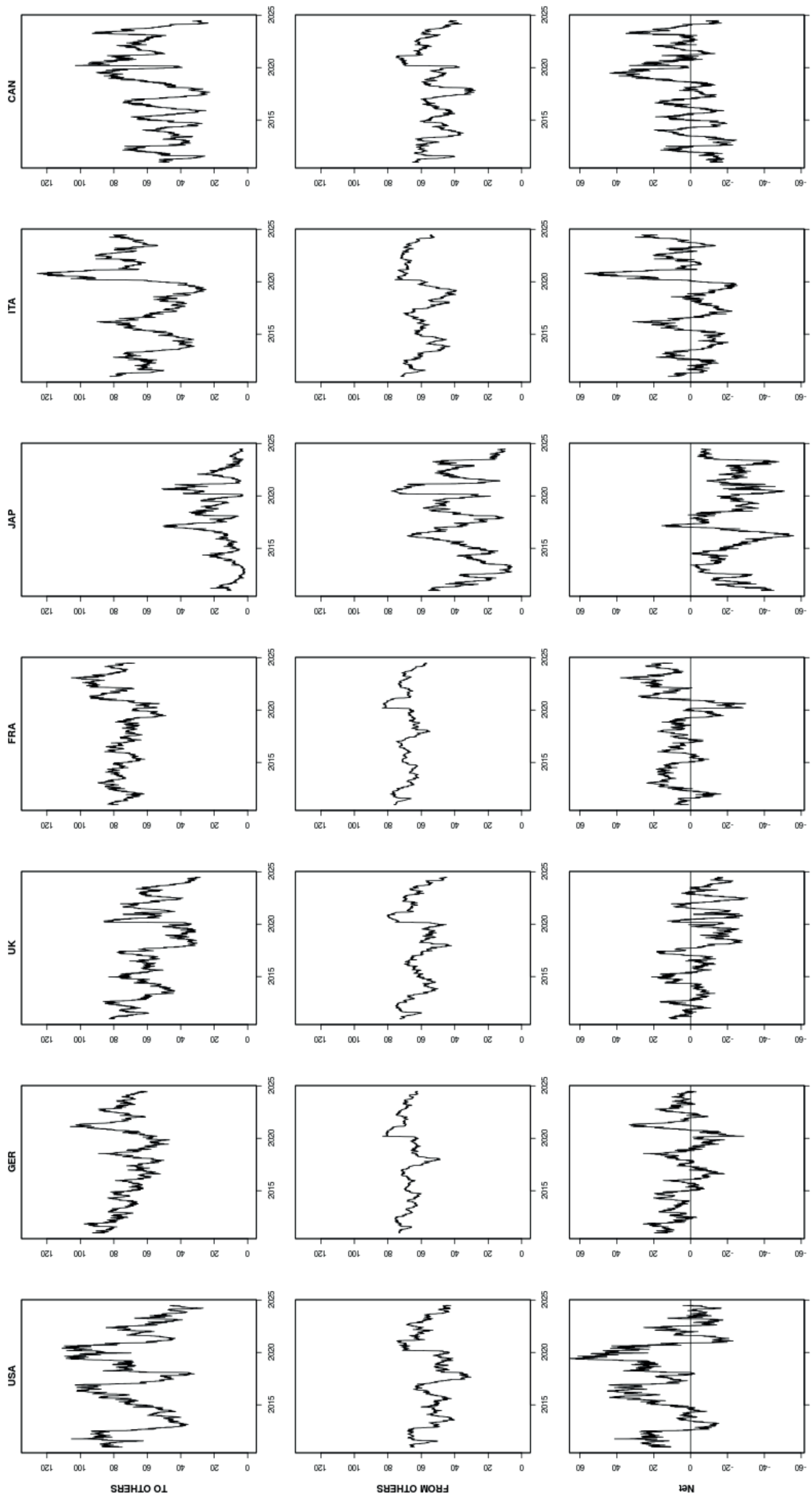

Fig. 3 Dynamic total directional and net connectedness indices

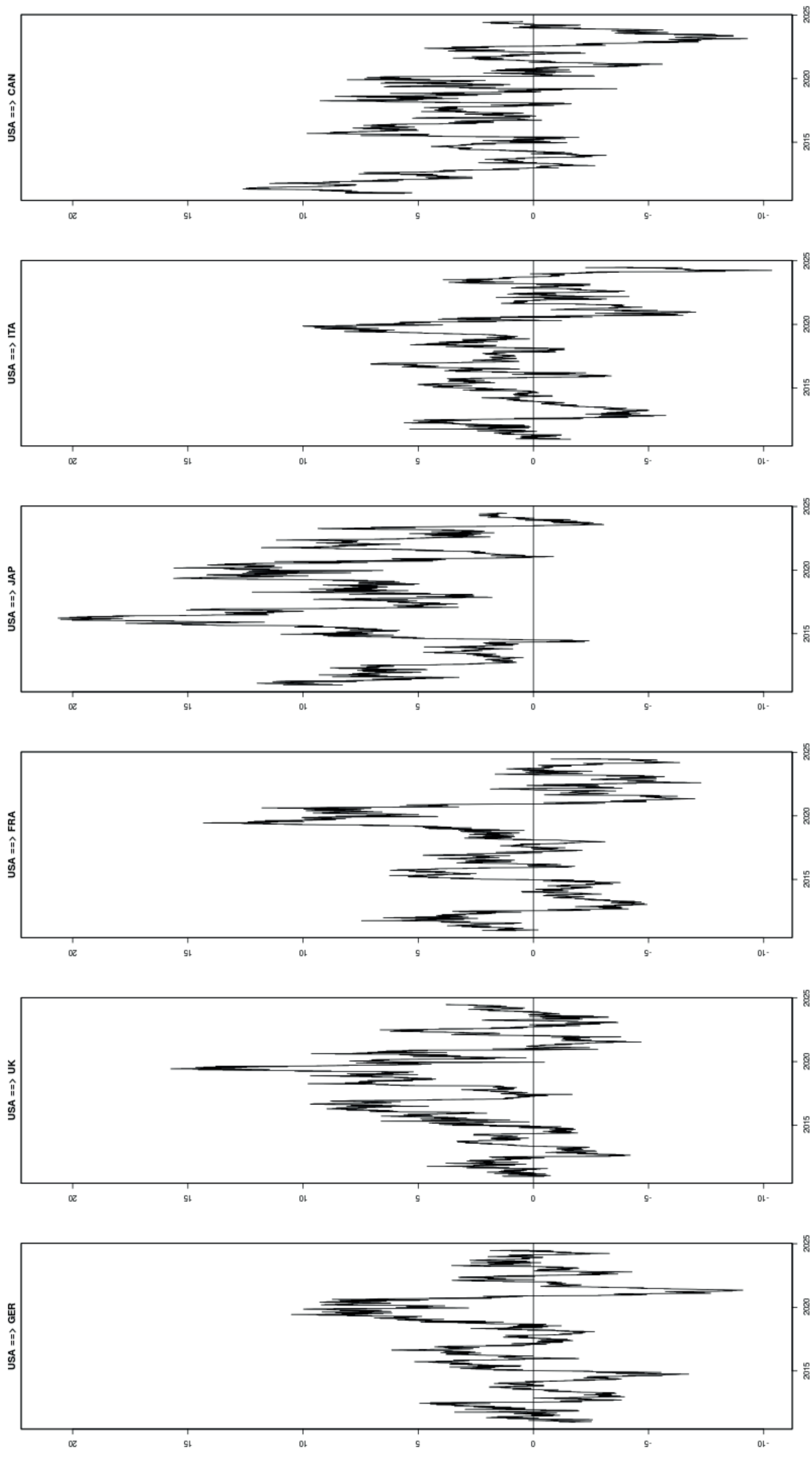

Fig. 4 Net connectedness from the USA to the other G7 countries

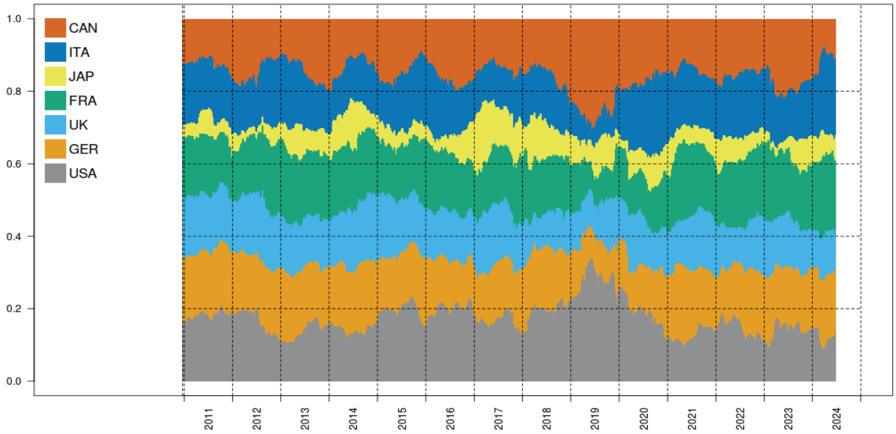

Fig. 5 Propagation values

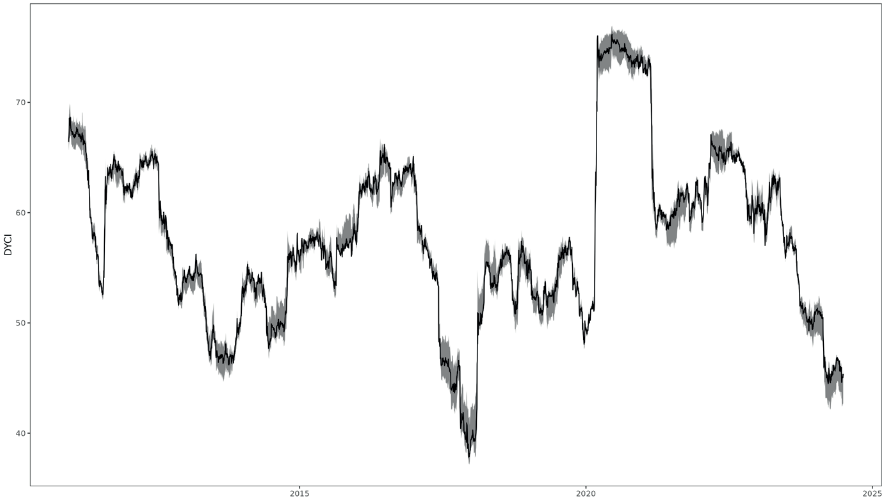

Fig. 6 DYCI: (shaded area: min & max of laglength 1-5), (solid line: VAR(3), selected)

References

Abildgren, K. (2016). A century of macro-financial linkages. *Journal of Economic Policy*, 8(4), 458–471.

Attilio, L. A., Faria, J. R., & Prado, M. (2024). The impact of the US stock market on the BRICS and G7: A GVAR approach. *Journal of Economic Studies, 51*(7), 1481–1506.

Barunik, J., & Krehlik, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2), 271–296.

Bates, D. S. (1991). The crash of '87: Was it expected? The information content of the volatility implied by options prices. *The Journal of Finance*, 46(3), 1009–1044.

Bekaert, G., & Harvey, C. R. (1995). Time-varying world market integration. *The Journal of Finance*, 50(2), 403–444.

Biswas, R., Loungani, P., Liang, Z., & Michaelides, M. (2024). Linkages between financial and macroeconomic indicators in emerging markets and developing economies. *Global Finance Journal*, 62, 101007.

Bonacich, P. (1987). Power and Centrality: A Family of Measures. *American Journal of Sociology*, 92, 1170–1182.

Bollerslev, T., Gibson, M., & Zhou, H. (2011). Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. *Journal of Econometrics*, 160(1), 235–245.

Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance*, 1, 223–236.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(1), 158–171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Financial Econometrics*, 14(1), 81–127.

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *The Journal of Business, 53*(1), 67–78.

Joaqui-Barandica, O., Gomez Daza, J. A., & Lopez-Estrada, S. (2024). Macro-financial interconnections in the Pacific Alliance: A quantile approach of stock markets and macroeconomic factors. *Applied Economics Letters*, 1–8.

Karanasos, M., Yfanti, S., & Hunter, J. (2022). Emerging stock market volatility and economic fundamentals: The importance of US uncertainty spillovers, financial and health crises. *Annals of Operations Research*, 313(2), 1077–1116.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in non-linear multivariate models. *Journal of Econometrics, 74*(1), 119–147.

Ma, Y., Wang, Z., & He, F. (2022). How do economic policy uncertainties affect stock market volatility? Evidence from G7 countries. *International Journal of Finance & Economics*. 27(2), 2303–2325.

Newman, M.E.J. (2010). *Networks: An introduction*. New York: Oxford University Press.

Ngene, G. M. (2021). What drives dynamic connectedness of the U.S. equity sectors during different business cycles? *The North American Journal of Economics and Finance*, 58, 101493.

Pesaran, M. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1), 17–29.

R Core Team. (2024). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/.

Ryan, J. A., & Ulrich, J. M. (2024). *quantmod: Quantitative financial modelling framework* (R package version 0.4.26). Retrieved from https://CRAN.R-project.org/package=quantmod.

Schmidbauer, H., Roesch, A., & Uluceviz, E. (2013). Market Connectedness: Spillovers, Information Flow, and Relative Market Entropy. Koç University-TUSIAD Economic Research Forum Working Paper, No. 1320, October.

Schmidbauer, H., Roesch, A., & Uluceviz, E. (2017). Frequency Aspects of Information Transmission in a Network of Three Western Equity Markets. *Physica A: Statistical Mechanics and its Applications*, 486, 933–946.

Schmidbauer, H., Roesch, A., Uluceviz, E., & Erkol, N. (2016). The Russian stock market during the Ukrainian crisis: A network perspective. *Czech Journal of Economics and Finance*, 66(6), 478–509.

Tahai, A., Rutledge, R. W., & Karim, K. E. (2004). An examination of financial integration for the group of seven (G7) industrialized countries using an I(2) cointegration model. *Applied Financial Economics*, 14(5), 327–335.

Uluceviz, E., & Yilmaz K. (2020). Real-financial Connectedness in The Swiss Economy. *Swiss Journal of Economics and Statistics*, 156(1).

Uluceviz, E., & Yilmaz K. (2021). Measuring Real-financial Connectedness in The U.S. Economy. *North American Journal of Economics and Finance*, 58(Nov.).

Wang, D., & Huang, W. Q. (2022). Forecasting Chinese macroeconomy with volatility connectedness of financial institutions. *Emerging Markets Finance and Trade*, 59(6), 1797–1817.

World Bank. (n.d.). *GDP (current US$)*. The World Bank. Accessed November 25, 2024. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=CA-IT-US-GB-DE-FR-JP.

Zhang, P., Sha, Y., & Xu, Y. (2021). Stock Market Volatility Spillovers in G7 and BRIC. *Emerging Markets Finance and Trade, 57*, 2107-2119.