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Network analysis of the foreign exchange market using minimum spanning trees constructed from the dynamic time warping distance measure

Joanna Małgorzata Landmesser-Rusek

Institute of Economics and Finance, Warsaw University of Life Sciences – SGGW, Poland

e-mail: joanna_landmesser@sggw.edu.pl

ORCID: 0000-0001-7286-8536

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Abstract: This paper evaluates the changes that occurred in the topological structure of the foreign exchange market due to the COVID-19 pandemic and after the Russian invasion of Ukraine. A network of 17 currencies was analysed from 1.01.2019 to 31.07.2022 in four sub-periods: before the pandemic, in the year of the pandemic outbreak, in the further course of the pandemic, and the year the war started. Dynamic time warping (DTW) distances between pairs of time series for individual currencies were calculated, and based on these distances, minimum spanning trees (MST) were constructed whose topological characteristics were then analysed. The results show that the topological structure of the foreign exchange market varied in the sub-periods studied. The financial crises caused by the COVID-19 pandemic and the Russian invasion of Ukraine affected the FX network in different ways. However, the two strongest monetary clusters (i.e. clusters centred on the USD and EUR, respectively) have still emerged. Comparing the MSTs for the crisis sub-periods, it can be seen that the USD took a dominant position during the pandemic outbreak, while the EUR played a more significant role during the war. This study contributes to the literature by characterising the topological structure of the FX market in specific sub-periods – during the COVID-19 pandemic and after the Russian invasion of Ukraine. Thus, it represents a particularly relevant study of the impact of crises on the global financial market.

Keywords: foreign exchange market, minimum spanning tree, dynamic time warping

1. Introduction

The exchange rate determines the relative level of a country's economic condition. It measures the economic balance between countries and often reflects their economic status. Exchange rates play an important role in international trade, which is crucial for any free market economy. For this reason, they are among the most analysed economic indicators in any country. The foreign exchange market is considered the most liquid and influences other markets. Fluctuations in exchange rates affect not only international trade activities and foreign investment but also financial transactions. The FX market is a complex system with many interconnections between currencies. For this reason, the foreign exchange market's characteristics and the currency network's topological structure should be studied.

The aim of the research was to assess the changes that occurred in the topological structure of the FX market due to the COVID-19 pandemic and after the Russian invasion of Ukraine. For this purpose, a network analysis of the foreign exchange market was carried out using minimum spanning trees (MSTs) constructed from the DTW distance measure. The distance was measured between pairs of time series for individual currencies, and topological features were analysed for the resulting trees. The author used data from stooq.com for 17 major currencies from 1.01.2019 to 31.07.2022. The analysis was conducted in four sub-periods:

- before the pandemic (from 1.01.2019 to 31.12.2019),
- in the pandemic outbreak year (from 1.01.2020 to 31.12.2020),
- in the subsequent course of the pandemic (from 1.01.2021 to 31.12.2021),
- and in the year of the war's outbreak (from 1.01.2022 to 31.07.2022).

In the study, the following research questions were posed:

1. Did the financial crises in the period under study affect the topological structure of the FX network?
2. Did the two crises caused by the COVID-19 pandemic and the Russian invasion of Ukraine equally affect the FX network?
3. Does the discovered topological structure of the network indicate the dominant position of any of the currencies (e.g. USD or EUR)?
4. What are the topological properties of the constructed MSTs in the analysed sub-periods?

This paper is organized as follows. Section 2 contains a literature review. Section 3 describes the methodology and the data used. Section 4 presents the empirical results, whilst Section 5 – a discussion of them. Section 6 concludes.

2. Literature review

The analysis of interactions between financial objects is usually carried out in correlation network approaches. Topological network analysis is a method that provides practical tools for interpreting market characteristics (Mantegna and Stanley, 2000; Djauhari and Lee, 2014). The structure of a network determines how different nodes are connected and how data are transmitted between these nodes. Minimum spanning trees, introduced to network theory by Kruskal (1956), compress information about the global network structure and simplify analysis by making the number of elements that need to be compared smaller. The application of MSTs to financial stock was introduced by Mantegna (1999), who proposed a network correlation analysis of the US stock market.

Moreover, the structural properties of the FX market have been studied using topological network analysis. Numerous authors have used MSTs in this regard. They have been applied to currency correlations, for example see McDonald et al. (2005). MSTs provide a meaningful description of global currency market *dynamics* and allow the identification of dominant and dependent currencies. Ortega and Matesanz (2006), using data from 28 countries, classified the effects of currency crises based on time series for exchange rates. Using linear correlation coefficients and the metric distance between pairs of countries, they constructed a hierarchical tree of countries by means of MST.

Naylor et al. (2007) used MSTs to extract a topological map for 44 currencies from 1995-2001. The technique generated a robust scale-free network. The topology proved stable during market crises and made it possible to discover relations for individual currencies and understand the dynamics of exchange rate determination. Górski et al. (2008) examined exchange rate correlation matrices for 60 currencies. MST graphs were presented, and inverse power-like scaling was discussed. The worst scaling was found for the USD. Górski et al. (2006) calculated MSTs and found clustering effects for strong currencies. Kwapień et al. (2009) also studied the topology of the FX market; based on the rates for 46 currencies from 1998-2008, they constructed different currency networks depending on the choice of the base currency. Their structure was not stable, but there were clusters of currencies that persisted over time. In the long-term trend, the USD node gradually lost its centrality while the EUR node became more central.

Feng and Wang (2010) studied the structural evolution of the Asian currency network, and found that the correlation between Asian currencies and the US dollar, previously a key regional currency, became weaker, and intra-Asian interactions intensified. Wang et al. (2013) examined the statistical properties of the FX network for the period 2007-2012 and confirmed that the USD and EUR were the dominant currencies; the Middle East cluster was stable, while the Asian cluster and the Latin America cluster were not. Fenn et al. (2012) also investigated dynamic communities in a currencies network, whereas Rešovský et al. (2013) compared MST representations of major world and European currencies, showing a large variation; in Central Europe, the Polish zloty was crucial. The central position of economies linked to China (Hong Kong, Singapore) was proved. The study by Limas (2019) was inspired by the MST methodology, analysed nine Latin American currencies and thus obtained a hierarchical tree with groups of exchange rates with similar co-movements.

In addition to the MST method, another way to build a network based on data dependency is the threshold method. Cao et al. (2020) proposed an optimal threshold strategy for creating a multilateral exchange rate correlation network for 33 currencies. The authors found that the international currency network has a community structure that consists of three currency areas: core, arbitrage, and shadow.

In most network evolution analyses, correlation is chosen as the preferred metric, but the dynamic time warping (DTW) measure can be a good alternative. The DTW method is used in many fields, such as biometrics (e.g. Tappert et al., 1990), bioinformatics (Aach and Church, 2001), data mining (Müller, 2007), computer animation (Arici et al., 2014) and finance (Stübinger, 2019). It has been used, for example, by Wang et al. (2012) and more recently, during the spread of the COVID-19 pandemic, by Gupta and Chatterjee (2020) to study the topology of the network of similarities between currencies.

Studies of the currency network evolution during periods of crisis are of particular interest. Jang et al. (2011) examined the time series properties of the FX market in the period 1990-2008 and analysed 61 currencies using the MST approach. They noted that the average correlation coefficient between currencies decreased during crises while the normalised tree length increased. After the 1997 Southeast Asian crisis, the EUR and USD had a strong negative correlation. The Asian and Latin American currencies moved away from the cluster centre (USD) during the Argentine crisis (1998-2002) and the Southeast Asian crisis.

The work mentioned above by Wang et al. (2012) used the DTW measure to examine the topology of the similarity network among 35 currencies. The analysis period of 2005-2011 was divided into three sub-periods: before, during, and after the US subprime crisis. Changes in the MST structure were analysed, and clusters of currencies resulting from the hierarchical trees in each sub-period were examined. It was concluded that the USD and EUR were the dominant currencies in the world. However, the USD gradually lost its central position, while the EUR behaved as a stable centre throughout the crisis. An approach based on the correlation network to study the dynamics of the FX market from 2005 to 2012 was proposed by Wang et al. (2014). The results indicate that financial crises in the analysed period significantly impacted on the network's topological structure and triggered a more central USD position in the MST.

Kazemilari et al. (2018) examined the topological network of the foreign exchange market from 2005 to 2011 regarding the subprime crisis. Structural changes before, during, and after the crisis were examined. The region-based network analysis uncovered significant changes in the constructed MSTs caused by the crisis. With a novel method based on the Jensen-Shannon divergence, Chakraborty et al. (2020) studied the association between currencies and analysed network clusters during periods of major international crises. The problem of globalisation in times of financial crises was studied by Miśkiewicz (2021), who found that during crises, exchange rate correlations increase, causing more cliques and higher ranks of nodes in the network.

The COVID-19 pandemic has affected the global economic system, including the currency market. Hatipoğlu (2021) examined the effects of the COVID-19 pandemic on the stock market network. Two MSTs were constructed before and during the pandemic based on DTW distances. Clusters of stock markets were found. Katsiampa et al. (2022) studied the co-movements and correlations between Bitcoin and 31 of the most tradable cryptocurrency assets, applying MSTs to data from the pre-COVID and COVID-19 periods. Studies on the evolution of the currency network in the context of COVID-19 are rare. However, to examine the currency market topology as the COVID-19 pandemic unfolded, Gupta and Chatterjee (2020) proposed a measure based on the lead-lag relation. The authors noted that as the crisis progressed, the 29 currencies analysed became highly interconnected, with the USD becoming more central in the currency market. The impact of COVID-19 on the FX market has been studied rather by other methods. For example, Devpura (2021) studied the relation between the EUR/USD exchange rate and the oil futures price using a predictive regression model. It was found that COVID-19 only impacted the exchange rate in March 2020.

Recently, the FX market has been affected by Russia's war with Ukraine, which broke out in February 2022. To the best of the author's knowledge, this is the first time anyone has studied the impact of the Russian invasion of Ukraine on the topological structure of the foreign exchange market network.

3. Methodology and data

3.1. Dynamic time warping method

DTW is an algorithm for comparing time series. It enables finding the smallest distance between two time series while allowing time transformation for both series (Bellman and Kalaba, 1959; Sakoe and Chiba, 1978; Rabiner et al., 1978). The distance measure based on the DTW algorithm is more suitable than the classical measure based on the Euclidean distance, particularly when comparing series with similar structures but shifted in time.

The purpose of the method is to compare two time series $X_1 = (x_{11}, \dots, x_{1N})$ and $X_2 = (x_{21}, \dots, x_{2M})$, which can be of different lengths. Keogh and Kasetty (2003) and Łuczak (2018) emphasised the necessity of normalising time series when using DTW.

First, the local distance measure $c_{ij} = c(x_{1i}, x_{2j}) = |x_{1i} - x_{2j}|$, $i = 1, \dots, N$, $j = 1, \dots, M$, is defined. It is treated as a cost function, and the task of optimal series matching is the task of finding a sequence of points that minimises the overall cost function. A matching path (warping path) is sought that passes through the low-cost areas and avoids the 'mountains' of high cost (Stübinger and Schneider, 2020). The warping path is sequence $w = (w_1, \dots, w_L)$, with $w_l = (n_l, m_l) \in \{1, \dots, N\} \times \{1, \dots, M\}$ for $l = 1, \dots, L$, $L \in \{max(N, M), \dots, N + M - 1\}$, satisfying the boundary, monotonicity, and step length conditions (Keogh and Ratanamahatana, 2005). The cost function associated with a certain warping path w has the form $c_w(X_1, X_2) = \sum_{l=1}^{L} c(x_{1n_l}, x_{2m_l})$.

The optimal warping path has the minimal cost associated with the matching. The optimal alignment between X_1 and X_2 is then given as:

$$DTW(X_1, X_2) = c_{w*}(X_1, X_2) = min\{c_w(X_1, X_2)|w \in W\} \quad (1)$$

where W is the set of all possible warping paths. The DTW method uses a dynamic programming algorithm to find optimal path w^* iteratively.

The similarities between exchange rate movements in the foreign exchange market are often measured by choosing correlation as the preferred metric, but the DTW measure is a good alternative to it.

3.2. Minimum spanning trees

The structural properties of the foreign exchange market can be studied using topological network analysis.

A mathematical representation of a network is a graph, a structure made of vertices (nodes) and edges. Formally, an undirected graph G is a pair $G = (V, E)$, where V is a set of vertices and E is a set of edges, which are two-element subsets of V : $E \subseteq \{(u, v): u, v \in V\}$. A weighted graph or a network is a graph in which each edge is assigned a weight that is some number (usually non-negative): $G = (V, E, w)$, where $w: E \to R$. In a connected graph, there is a path for each vertex to any other vertex. A tree is an undirected graph that is connected and acyclic, i.e. there is a path between any two vertices and it is the only possible path between them.

The spanning tree of graph $G = (V, E)$ is a tree that contains all the vertices from set V, and the set of edges of the tree is a subset of set E. If a graph has $|V|$ vertices, then its spanning tree has $|E| = |V| - 1$ edges. For a weighted, undirected graph $G = (V, E, w)$, a minimum spanning tree (MST) is called spanning tree T, for which the sum of the weights of all edges:

$$w(T) = \sum_{(u,v)\in T} w(u, v) \quad (2)$$

is minimal (this is a spanning tree of minimal cost).

Two greedy algorithms are used to find MST: Kruskal's edge-based and Prim's node-based. In the latter, the tree starts from one arbitrary node and grows from that node with each step while checking the required conditions (Prim, 1957).

3.3. Topological characteristics of networks

In order to study the structure of networks, researchers use topological indices of networks found through constructed MSTs. The most commonly used indices are:

- mean degree, the average number of edges per vertex in the graph (the degree of the vertex refers to the number of edges attached to the node);
- graph density - the proportion of present edges from all possible edges in the network; it is an indicator of how well connected the vertices of the graph are;

$$density(G) = \frac{|E|}{|V|(|V|-1)/2} \quad (3)$$

- maximum degree, the degree of the vertex with the greatest number of edges incident to it;
- mean distance (average path length), the average distance between all pairs of nodes in the graph; the mean of the lengths of the shortest paths $dist(u, v)$, $u, v \in G$, between all pairs of vertices in the network (Wang et al., 2014).

$$APL(G) = \frac{\sum_{v,u} dist(v,u)}{|V|(|V|-1)/2} \quad (4)$$

This indicator measures the efficiency of information flow in the network. It helps distinguishing between networks that are easy to pass through and those that are complex and inefficient. It can point to a structure that is susceptible to infection by the effects of negative financial events (Denkowska and Wanat, 2021);

- diameter – length of the longest shortest path between any pair of nodes. If the diameter shrinks, the distance between the most distant vertices decreases, which favours the transfer of information in the network (Li et al., 2018).

$$diameter(G) = \max_{u,v} dist(v,u) \tag{5}$$

A key concept in network analysis is the measure of centrality, which refers to the position of the nodes in the network (Freeman, 1979; Kazemilari and Mohamadi, 2018). It allows the network to be divided into important and unimportant nodes. Centrality indices can be considered in local and global terms. For each vertex separately can be determined:

- betweenness, centrality based on the position of the broker connecting others. It shows the frequency of a node in the shortest paths between indirectly linked nodes (how many times a node plays the role of a bridge over the shortest path between two other nodes).

$$C_B(v) = \sum_{i \neq j \neq v}^{|V|} \frac{\sigma(i,j|v)}{\sigma(i,j)} \tag{6}$$

where $\sigma(i,j)$ is the amount of shortest paths in the network and $\sigma(i,j|v)$ is the amount of those paths that go through v. It indicates the most critical nodes of a network. A node with high betweenness has more control over the network;

- closeness, measures how many steps it takes to access every other vertex from a given vertex; the inverse of the distance between a node and all other nodes. It helps find central vertices within a single cluster. The more central a vertex is, the closer it is to all other vertices and the higher the closeness value;

$$C_C(v) = \frac{1}{\sum_{i=1}^{|V|} dist(v,i)} \tag{7}$$

- strength, the sum of neighbouring edge weights for each vertex.

Global centrality measures take into account the entire network. This article uses the following measures of centrality at network level:

- degree centrality, the graph's centralisation index regarding the nodes' number of links. Its higher value indicates a higher risk that nodes will intercept anything that flows through the network;
- closeness centrality, an indicator of graph centralisation concerning the closeness of nodes (understood as the average length of the shortest path between a node and all other nodes in the graph);
- assortativity, evaluates how vertices in a network are linked to each other, i.e. whether the high-degree (or correspondingly low-degree) nodes connect to high (low) degree nodes (Newman, 2002, 2003). It takes values in the range (-1,1). Negative assortativity means that high-degree vertices merge into low-degree vertices (network structure of stars with hubs); positive assortativity means that high-degree vertices coincide with high-degree vertices. It informs about network resistance to the random spread of crises;
- modularity, measures intra-community connections versus inter-community connections. It takes values in the range (-1,1). High modularity reflects dense intra-community and sparse inter-community connections.

Based on the network topology, a hierarchical community structure can be built using the Girvan-Newman method. The edge betweenness used in the method is based on the number of shortest paths between all pairs of nodes passing through an edge. The Girvan-Newman method uses the observation that edges between groups tend to have a higher value of edge betweenness than those within groups

(Newman and Girvan, 2004). The algorithm calculates the edge betweenness of all network edges and removes the edges with the highest value of the betweenness measure.

The MSTs constructed in this article can reveal the roles of individual currencies. The topological indices of the MSTs make it possible to assess the importance of individual currencies in the entire network.

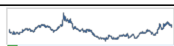
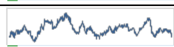
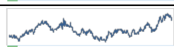
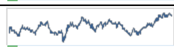
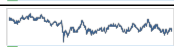
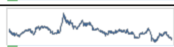
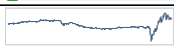
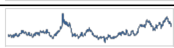
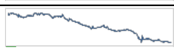
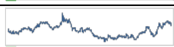
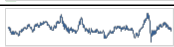
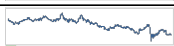
3.4. Data

Daily exchange rate data for 17 currencies against the New Zealand dollar (NZD) was obtained from https://stooq.pl/ and included the following currencies: USD, EUR, JPY, GBP, CHF, CAD, AUD, SEK, NOK, DKK, RUB, CNY, TRY, SGD, CZK, HUF, PLN for the period from 1.01.2019 to 31.07.2022 (n = 934 days).

The X/NZD exchange rate expresses a unit of currency X in units of NZD. In the analysis, NZD acts as a numeraire currency. The NZD base means treating this currency as a reference and excluding it from the network. The choice of numeraire is problematic because currencies are valued against each other, so there is no independent numeraire. There is no standard solution, and less popular currencies or gold are often considered. NZD was chosen because this currency is of marginal importance to the FX market. The choice of NZD as a numeraire makes the analysis comparable to Naylor et al. (2007), Wang et al. (2012), and Gupta and Chatterjee (2020).

Table 1 presents descriptive statistics for the currency exchange rates against the NZD and miniaturised graphs of the analysed time series.

Table 1. List of 17 investigated currencies and descriptive statistics for their exchange rates against NZD with their visualization

Symbol	Name of the currency	Mean	Max	Min	SD	CV	Dynamics
USD	U.S. Dollar	1.498	1.780	1.344	0.076	0.051	
EUR	Euro	1.699	1.907	1.571	0.054	0.032	
JPY	Japanese Yen	0.013	0.016	0.011	0.001	0.072	
GBP	UK Pound Sterling	1.953	2.096	1.837	0.047	0.024	
CHF	Swiss Franc	1.579	1.804	1.447	0.064	0.041	
CAD	Canadian Dollar	1.151	1.258	1.074	0.038	0.033	
AUD	Australian Dollar	1.065	1.116	1.007	0.020	0.019	
SEK	Swedish Krona	0.163	0.176	0.147	0.005	0.030	
NOK	Norwegian Krone	0.166	0.179	0.151	0.005	0.029	
DKK	Danish Krone	0.228	0.255	0.211	0.007	0.031	
RUB	Russian Rubel	0.021	0.030	0.010	0.003	0.132	
CNY	Chinese Yuan	0.223	0.248	0.208	0.007	0.032	
TRY	Turkish Lira	0.197	0.283	0.086	0.062	0.316	
SGD	Singaporean Dollar	1.098	1.225	1.019	0.039	0.035	
CZK	Czech Koruna	0.066	0.071	0.062	0.001	0.022	
HUF	Hungarian Forint	0.005	0.005	0.004	0.000	0.072	
PLN	Polish Zloty	0.380	0.424	0.319	0.020	0.052	

Note: SD – standard deviation, CV – coefficient of variation.

Source: own elaboration based on data from https://stooq.pl.

During the pandemic, the USD proved to be a safe haven for uncertain times. Acting as the main currency in international currency markets, it strengthened against almost all currencies. The currencies of emerging markets and commodity exporters experienced the most significant depreciation. The reopening of economies contributed to a reduction in demand for the US dollar, but in 2021 the dollar began to strengthen again in response to expected Fed monetary policy. The EUR was stronger in 2020 but began to depreciate at the beginning of 2021. Important factors influencing exchange rate changes in 2021 included local economic conditions and vaccination campaigns in individual countries.

When Russia attacked Ukraine in February 2022, there was immediate panic in the markets. The closeness of the war and interest rate hikes in the USA created pressure in the Eurozone. Investors overreacted to the initial threat, but the trend continued. The currencies that have suffered the greatest cost of sanctions have lost the most. For this reason, the euro weakened against the dollar. The Polish zloty, the Czech koruna, and the Hungarian forint were also in retreat. Safe havens such as the US dollar and the Swiss franc gained in value.

As mentioned above, the analysis was conducted in four sub-periods with the following number of observations:

- before the pandemic (2019) – 256 observations,
- in the year of the outbreak of the pandemic (2020) – 259 observations,
- in the further course of the pandemic (2021) – 259 observations,
- in the year of the war outbreak (2022) – 160 observations.

All the currency time series were smoothed using a 5-day moving average. Before calculating the distances between the studied currencies using the DTW method, the series were normalised by standardisation (achieving unit variance and zero mean).

4. Results

First, using the DTW algorithm, a distance matrix was calculated to measure the similarity between each pair of currencies. An example alignment between the two selected time series for the USD and EUR is presented in Figure 1.

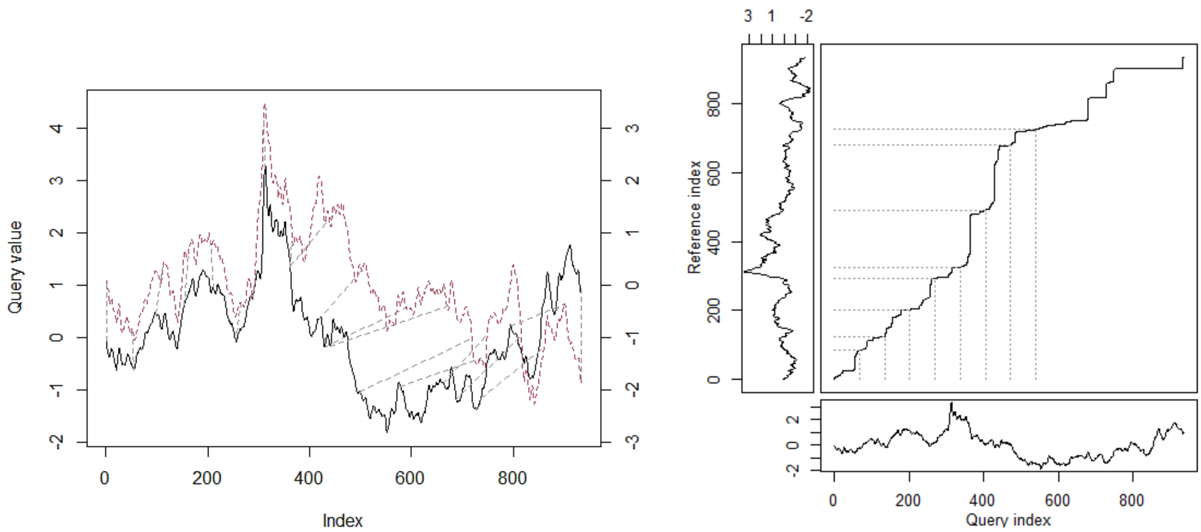


Fig. 1. Alignment between time series for two currencies: USD and EUR

Note: Left panel: solid black line – USD/NZD exchange rate, dashed grey line – EUR/NZD; right panel: query index for USD, reference index for EUR.

Source: own elaboration in R.

The left panel in Figure 1 shows the time series plots with the alignment. The solid black line represents the USD/NZD exchange rate, and the dashed grey line stands for EUR/NZD rate. The right panel presents a three-way plot of the time series alignment (query index for USD, reference index for EUR) with the optimal warping path in the middle. The shape of the warping path provides information about the pairwise correspondence of time points, and the distance value is the cost associated with the matching.

The DTW method allowed the currency time series to be mutually compared in four sub-periods: before the pandemic, in the pandemic outbreak year, in the subsequent course of the pandemic, and the year of the war's outbreak (i.e. 2019, 2020, 2021 and 2022). The resulting distance matrices were then used to construct four minimum spanning trees presented in Figure 2.

The number of vertices in each constructed tree amounted to 17, the number of edges was 16, the graph density was 0.12, the average vertex degree was 1.88, and the maximum vertex degree was 4.

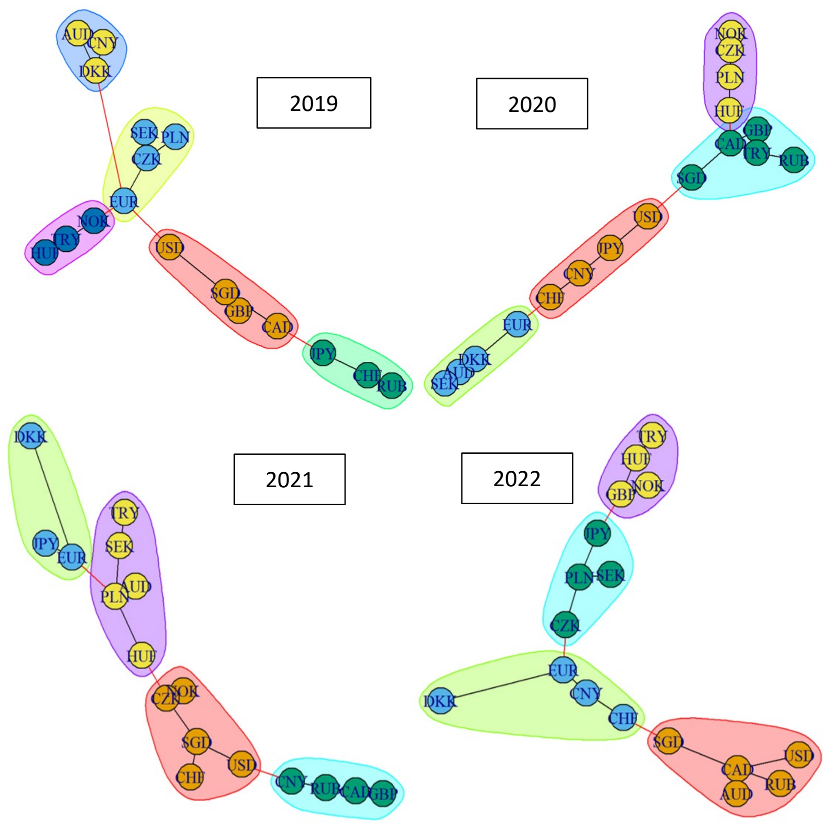


Fig. 2. Minimum spanning trees for the currency networks in 2019, 2020, 2021 and 2022

Note: The related currencies are displayed in the same colour.

Source: own elaboration.

The constructed trees cover four long sub-periods of the entire analysis time. However, the relations in the FX market are worth examining in a dynamic way. For this purpose, numerous MSTs were built using the rolling window technique with a width of four months and a seven-day step. For the 171 networks obtained in this way, the values of basic topological characteristics such as mean distance (average path length), diameter, degree centrality, closeness centrality, assortativity, and modularity, were determined and presented in graphs (see Figure 3).

The panels of Figure 3 show white and grey vertical bars corresponding to the successive analysed years: 2019, 2020, 2021, 2022. It should be noted that MSTs of the FX market present various topological properties in times of crises (2020 and 2022), and beyond those (2019 and 2020). A lower average distance between graph nodes and a higher degree of graph centralisation characterises the period before the pandemic (2019). After the pandemic outbreak (2020) and in the year the war started (2022), the mean distances between the nodes increased, diameters showed larger values, and the centralisation of graphs decreased. During both crises, the currencies were less linked to each other, and the structure of MSTs was less correlated than before. The lower degree centrality values indicate that nodes are less likely to intercept everything that flows through the network. Despite this, it should be noted that the currency network showed negative assortativity (star structure with hubs) for most of the period studied. The relatively high modularity of the network partitioning reflects the dense connections within communities and the sparse connections between them.

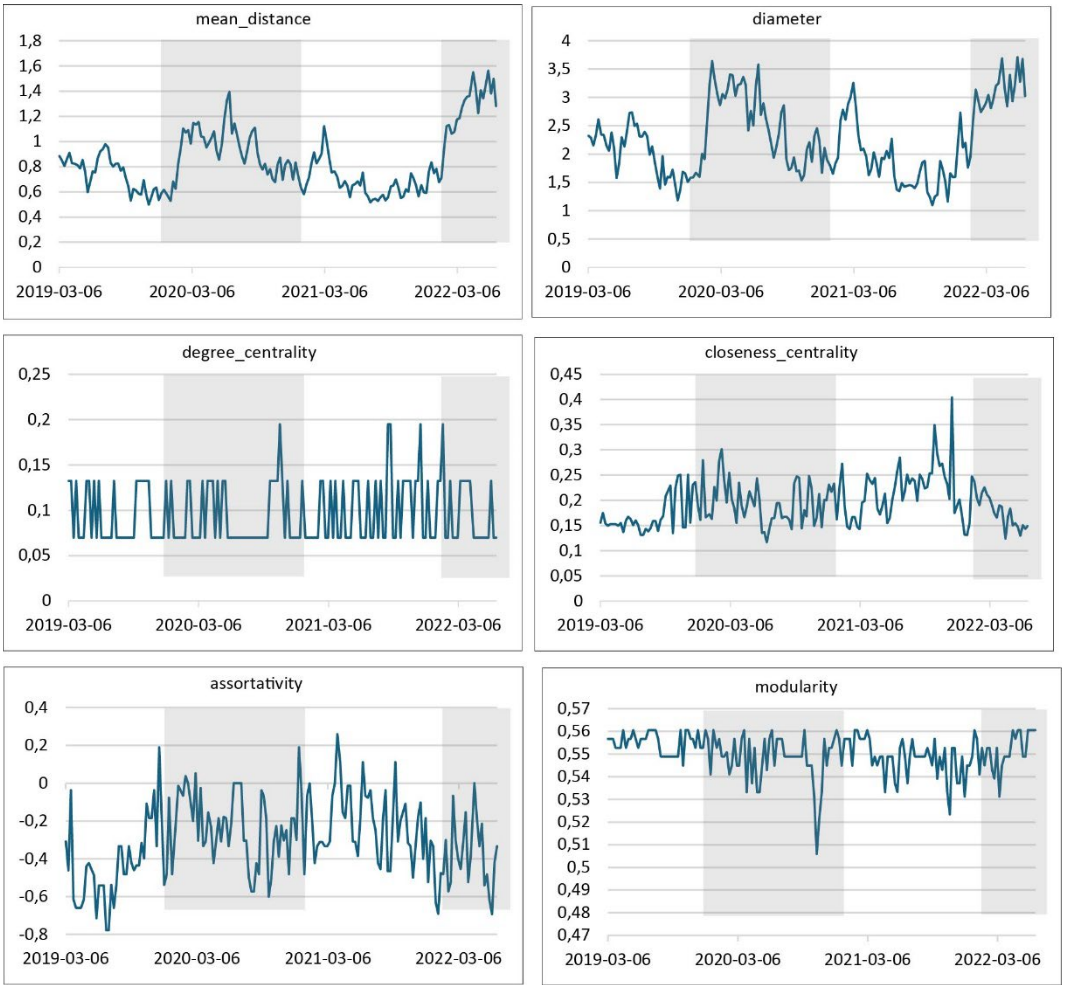


Fig. 3. Plots of selected topological characteristics of MSTs constructed for the FX market

Note: The white and grey vertical bars correspond to successive years of the analysis.

Source: own elaboration.

In the next step, the author performed community detection using the Girvan-Newman algorithm based on edge betweenness (see Ognyanova, 2016). The detected currency groups consist of more closely connected nodes with fewer connections between groups. In the panels of Figure 2, related currencies are in the same colour.

In 2019, five subgroups of currencies were noted. Two of them occupied the central position in the constructed MST: one with EUR at its centre, and the other with USD. The former is composed of EUR, CZK, PLN, and SEK. The latter includes USD, SGD, GBP, and CAD. The outbreak of the COVID-19 pandemic in 2020 reduced the number of subgroups to four. While the group concentrated around the U.S. dollar (this time made up of such notable currencies as USD, JPY, CNY, and CHF) continued to play a significant role in currency intermediation, the role of the EUR group (EUR together with DKK, AUD, SEK) became peripheral. A possible interpretation of the EUR's distancing from the centre is that the EUR, unlike the USD, is not seen as a safe haven that can store value during a violent crisis. This confirms the thesis of the USD being the predominant currency in the FX market during periods of crises (previously, similar results were obtained, for example, in Wang et al. (2014), Gupta and Chatterjee (2020)).

Table 2. Selected characteristics for nodes in 2019, 2020, 2021, 2022

	2019				2020			
	degree	between-ness	closeness	strength	degree	between-ness	closeness	strength
USD	2	60	0.16	0.22	2	63	0.11	0.20
EUR	4	90	0.17	0.61	2	39	0.08	0.18
JPY	2	28	0.11	0.18	2	60	0.11	0.28
GBP	1	0	0.10	0.23	1	0	0.09	0.11
CHF	2	15	0.10	0.29	2	48	0.09	0.30
CAD	2	39	0.13	0.20	4	77	0.11	0.72
AUD	1	0	0.12	0.15	2	15	0.05	0.82
SEK	1	0	0.08	0.31	1	0	0.04	0.39
NOK	2	28	0.10	0.64	1	0	0.05	0.37
DKK	3	29	0.16	0.48	2	28	0.08	0.49
RUB	1	0	0.08	0.21	1	0	0.07	0.10
CNY	1	0	0.09	0.30	2	55	0.10	0.34
TRY	2	15	0.07	0.64	2	15	0.08	0.39
SGD	3	59	0.15	0.42	2	64	0.11	0.20
CZK	3	29	0.14	0.56	2	15	0.07	0.56
HUF	1	0	0.05	0.33	2	39	0.09	0.36
PLN	1	0	0.11	0.12	2	28	0.08	0.35
	2021				**2022**			
	degree	between-ness	closeness	strength	degree	between-ness	closeness	strength
USD	2	48	0.06	0.38	1	0	0.06	0.07
EUR	3	29	0.06	0.45	3	71	0.09	0.58
JPY	1	0	0.05	0.26	2	48	0.08	0.29
GBP	1	0	0.03	0.26	3	41	0.07	0.58
CHF	1	0	0.05	0.32	2	55	0.07	0.49
CAD	2	15	0.04	0.60	4	42	0.06	0.51
AUD	1	0	0.05	0.24	1	0	0.05	0.19
SEK	2	15	0.05	0.63	1	0	0.07	0.18
NOK	1	0	0.05	0.38	1	0	0.06	0.28
DKK	1	0	0.06	0.02	1	0	0.09	0.02
RUB	2	28	0.05	0.64	1	0	0.06	0.14
CNY	2	39	0.06	0.46	2	60	0.08	0.69
TRY	1	0	0.04	0.38	1	0	0.05	0.21
SGD	3	65	0.07	0.88	2	48	0.07	0.32
CZK	3	71	0.07	1.15	2	63	0.09	0.28
HUF	2	63	0.07	0.70	2	15	0.06	0.36
PLN	4	71	0.07	0.92	3	65	0.09	0.45

Note: The grey background indicates those currencies for which the value of the corresponding measure is one of the highest.

Source: own elaboration.

The year 2021 could be called the year of the Eastern European currencies. The opening up of the economies after their previous freeze and the implementation of vaccination campaigns led to changes in the currency market. Eastern European currencies such as the PLN, HUF, and CZK formed a new centre; the EUR and USD moved slightly away from them. However, the Russian invasion of Ukraine in 2022 led to an increase in the role of the EUR in the market (in a cluster with the CNY, CHF, and DKK). It can be seen that EUR, PLN, and CZK remain under intense pressure from the ongoing war, whilst EUR became a hub and broker (bridge) connecting other currencies. It took over the position of the central vertex, where the USD had been for years. The USD's distance from other currencies (in the periphery along with the SGD, CAD, RUB, and AUD) is explained by its tendency to strengthen, while the EUR and most other European currencies have been weakening since the outbreak of the war.

Finally, local centrality indices were determined for each currency each year, making it possible to divide the network into important and unimportant nodes. Table 2 indicates the values of such characteristics as betweenness, closeness, strength, and additionally, the degree of each node.

In 2019, two currencies had a central position: EUR and USD. Both betweenness and closeness reached their highs, indicating that both currencies acted as brokers and quickly reached other vertices. The pandemic outbreak caused a decline in EUR intermediation, while the USD remained an important player. In addition to the USD, the CAD, and SGD proved their relevance. The most central and brokered position in 2021 was occupied by CZK, PLN and SGD, undermining the role of USD. These three currencies scored highest on degree, betweenness, closeness, and strength centrality measures. The Russian-Ukrainian conflict has had a major impact on the European currency market in 2022, causing a considerable increase in the centrality of the EUR and regional currencies of lesser importance, such as the PLN and CZK. There have been evident changes in the position of individual currencies in the FX market as a result of both the COVID-19 and war crises. During the pandemic outbreak, the USD took a dominant position, while the EUR plays a more significant role during the war.

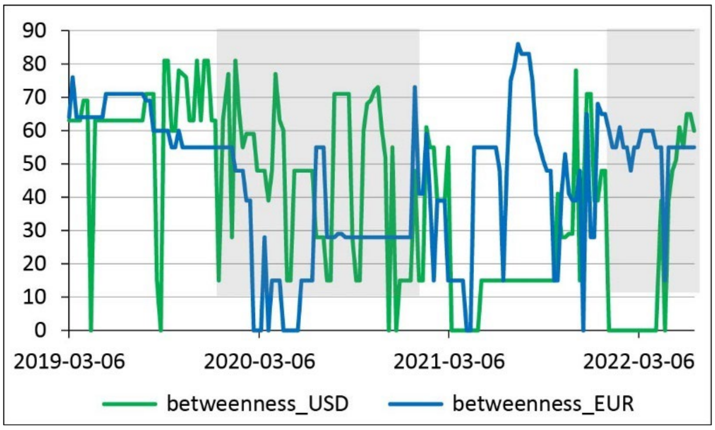


Fig. 4. Changes in the values of the betweenness coefficient for two main currencies: the USD and EUR

Source: own elaboration.

Figure 4 illustrates the changes in the betweenness coefficient for the USD and EUR over the entire time interval using the rolling window technique (with a width of four months and a step of seven days).

Based on Figure 4, one can again conclude that the EUR had strong control over the currency network, but its position weakened during the COVID-19 crisis. With the recovery of the global economy, its status has rebounded. The USD occupied a crucial status in the network, which weakened during the late pandemic and immediately after the outbreak of the war.

5. Discussion

The impact of the crisis periods in recent years on the topological structure of the currency network was considered in this work. As many other researchers, the other derived a hierarchical taxonomy of currencies by constructing minimum spanning trees. A cluster structure of currencies was found, and key currencies in the market were identified.

Analysing the topological features of the built networks, it was found that the MSTs of the FX market present different characteristics depending on the state of the economies. The determined values of the topological properties of the constructed MSTs answer research question No. 4. As expected, the empirical results indicated a different FX market structure in the sub-periods studied. Thus, the study answered research question No. 1 positively. The results obtained suggest different exchange rate dynamics in and out of crises. However, the constructed network structure indicates that two currencies still dominate the market: USD and EUR, especially during crises (research question No. 3).

On starting the research, the author expected confirmation that the US dollar would have proved to be a safe haven during the Covid-19 pandemic. For 2022, when Russia attacked Ukraine, strong pressure on European currencies was expected. The network analysis methods used in this study allowed to obtain some clues in this regard. Based on the constructed MSTs, it could be checked whether there was a concentration of currencies around the USD after the outbreak of the COVID-19 pandemic (a result previously obtained by Gupta and Chatterjee, 2020). The results confirm the USD's dominant role at this time. However, the turbulence caused by the outbreak of the war in Ukraine in its initial phase is different, and the crisis caused by it did not bring the USD back to the role of a central currency. Both crises, caused by the COVID-19 pandemic and the Russian invasion of Ukraine, affected the FX network unequally (this is the answer to research question No. 2).

Researchers have already been engaged with monitoring the role of the USD in the FX market. For example, Kwapień et al. (2009), studying the currency network over the long term, showed that the USD is losing its position while the EUR is becoming more central. The rise of the EUR node was possible because the EUR has become a more influential currency and acts as an alternative to the USD. This time, however, it should be taken into account that the change in the position of the USD is due to a special event – the outbreak of war in Europe, which puts European currencies in a particular role. Some studies, such as Mizuno et al. (2006), indicated the importance of the geographic region to the structure of the global currency network. Wang et al. (2013) suggested that currencies can be grouped by geographical or trade criteria, pointing to the international and European clusters, in which the USD and EUR are the predominant currencies. Moreover, this analysis indicates a regional linkage of European currencies (EUR, PLN, CZK, HUF, DKK, SEK, which are often found in common clusters), and a trade partnership relation with the USD (e.g. SGD, CAD, AUD, JPY).

6. Conclusions

This paper analysed complex international foreign exchange market relations using daily data from January 2019 to July 2022. The purpose of the study was to assess the changes that occurred in the topological structure of the FX market due to the COVID-19 pandemic and after the Russian invasion of Ukraine. Minimum spanning trees were built for the currency network based on the DTW distances between currency time series. Topological measures of the obtained trees were also further analysed. The network's topological properties in times of crises (2020 and 2022) and beyond (2019 and 2020) were diverse. In the pandemic year (2020) and the year of the war's outbreak (2022), the average distances between the nodes increased, and graph centralisation decreased. For most of the period studied, the currency network had a star structure with hubs. The relatively high modularity reflects the dense connections within communities.

The analysis revealed that in 2019, the USD and the EUR occupied the central position in the constructed MST. With the pandemic outbreak, the USD began to play a more important role in currency intermediation, and the role of the EUR diminished. The year of 2021 was the year of Eastern European currencies, when the currencies such as PLN, HUF, and CZK formed a new centre, while EUR and USD moved away from it. However, the outbreak of the Russian war caused the EUR to play a critical role, becoming a hub and broker connecting other currencies. The growing distance of the USD against other currencies can be justified by its high tendency to strengthen (in contrast to the depreciating EUR and other European currencies).

As a result of the crises caused by the COVID-19 pandemic and the Russian invasion of Ukraine, changes occurred in the FX network. Nevertheless, the two strongest monetary clusters (i.e. those whose centres are USD and EUR, respectively) are still emerging. Comparing the two MSTs for the crisis sub-periods, it can be seen that during the pandemic outbreak, the USD took a dominant position, while during the war, the EUR plays a more significant role.

This work was inspired by the minimum spanning tree methodology, which provides a simple way to visualise relations in the foreign exchange market. The method's strength is that MSTs contain basic information about the global structure of the network since their construction is based on the strongest links between nodes. As Naylor et al. (2007) noted, this method is useful in "determining the underlying relationships for individual currencies and to understanding the dynamics of exchange rate price determination as part of a complex network." However, it should be pointed out that different base currencies can generate completely different structures in the FX market (Kwapień et al., 2009). The methods used also have their limitations. For example, the DTW helps compare time series, but the calculated distance depends on the time series' duration and magnitude. In particular, to make meaningful comparisons between two time series, both must be normalised. Therefore, the method of normalisation affects the final result.

The scientific literature on foreign exchange markets consists primarily in publications devoted to local markets or key currencies separately. In doing so, it focuses mainly on forecasting their exchange rates. This article presents a holistic approach, where the network structure of the global foreign exchange market was analysed. This research contributes to the literature by describing the topological structure of the FX market in specific sub-periods, namely during the COVID-19 pandemic and after the Russian invasion of Ukraine. Thus, it represents a particularly relevant study of the impact of crises on the global financial market.

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