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Relationship between the COVID-19 pandemic and currency exchange rates studied by means of the Dynamic Time Warping method[1]

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Abstract. The COVID-19 pandemic affected the entire global economic system, including currency exchange rates. The main objective of this study is to assess the similarity between time series of currency exchange rates before and during the COVID-19 crisis. In addition, the study aims to examine the relationship between the exchange rates of currencies and the COVID-19 time series in particular countries. The Dynamic Time Warping (DTW) method was applied to check if changes in the exchange rates were related to the spread of COVID-19, and if they were, to what extent it was so. The use of the DTW allows the calculation of the distance between analysed time series. In this study, it made it possible to group the analysed currencies according to their change relative to the pandemic dynamics. The study is based on data from the Stooq and Our World in Data websites. Data on the 17 studied currencies denominated in the New Zealand dollar came from the period between 1 January 2019 and 10 November 2021, and the COVID-19 data from the period between 1 March 2020 and 10 November 2021. The results demonstrate that exchange rates evolved differently in all the three analysed periods: the pre-pandemic period and the first and the second phase of the pandemic. The outbreak of the pandemic led to the concentration of most currencies around the US dollar. However, when the economies unfroze, a polarisation of the currency market occurred, with the world's major currencies clustering either around the US dollar or the euro.

Keywords: currency exchange rates, COVID-19 pandemic, Dynamic Time Warping, DTW
JEL: C58, C32, C38

Ocena zależności między pandemią COVID-19 a kursami walut za pomocą metody Dynamic Time Warping

Streszczenie. Pandemia COVID-19 wpłynęła na światowy system gospodarczy, w tym na kursy walut. Głównym celem badania omawianego w artykule jest ocena podobieństwa pomiędzy szeregami czasowymi kursów walut przed pandemią i w jej trakcie. Ponadto podjęto próbę

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zbadania relacji pomiędzy kursami walut a szeregami czasowymi dotyczącymi pandemii COVID-19 w poszczególnych krajach. Aby sprawdzić, czy i w jakim stopniu zmiany kursów walut są związane z rozprzestrzenianiem się COVID-19, zastosowano metodę dynamicznego marszczenia czasu (Dynamic Time Warping – DTW), umożliwiającą obliczenie odległości pomiędzy analizowanymi szeregami czasowymi. Pozwoliło to na pogrupowanie walut według ich zmian w stosunku do dynamiki pandemii. W badaniu wykorzystano dane pochodzące z serwisów internetowych Stooq i Our World in Data. Dane dla 17 walut denominowanych w dolarach nowozelandzkich pochodzą z okresu od 1 stycznia 2019 r. do 10 listopada 2021 r., a dane o pandemii COVID-19 – z okresu od 1 marca 2020 r. do 10 listopada 2021 r. Stwierdzono, że kursy walut kształtowały się odmiennie w okresie przed pandemią oraz w jej pierwszej i drugiej fazie. Wybuch pandemii doprowadził do koncentracji większości walut wokół dolara amerykańskiego (USD). Po odmrożeniu gospodarek nastąpiła polaryzacja rynku walutowego, na którym główne waluty świata skupiły się albo wokół USD, albo wokół euro.

Słowa kluczowe: kursy walut, pandemia COVID-19, dynamiczne marszczenie czasu, DTW

1. Introduction

COVID-19 has been a huge shock to the entire global economic system. Disease outbreaks are usually unexpected, and their impact cannot be predicted with certainty. The associated negative sentiments or panic might influence markets significantly, leading to crises. The COVID-19 pandemic caused the contraction of the global economy in the first half of 2020. To offset the damaging effects of the virus, governments supported economies through direct and indirect fiscal spending, and central banks began monetary easing. For many developing economies, the global shock caused significant capital outflows and downward pressure on the value of their currencies. The recovery of the world economy in the second half of 2020 led to the reversal in exchange rates. However, the COVID-19 crisis continued to affect the current accounts of many countries in 2021.

Numerous academic studies have concluded that the COVID-19 pandemic had a significant impact on the financial market, including currency exchange rates. Actually, exchange rates were one of the asset prices most affected by the pandemic. Iyke (2020) argued that some valuable information which can be used to predict returns and volatility of particular currencies could be inferred from the outbreak of the pandemic. He used the total numbers of infections and deaths per million people to demonstrate that COVID-19 has a better predictive power over volatility than over returns for a one-day-ahead forecast horizon, while as regards a five-day-ahead forecast horizon, the opposite holds true. This evidence points to a new prediction channel for exchange rates, namely the pandemic channel. In another study, Feng et al. (2021) examined the impact of COVID-19 on the exchange rate volatility in 20 countries in the period from 13 January to 21 July 2020, using a systematic

GMM estimation. The empirical results indicated that rising numbers of confirmed cases significantly increase the exchange rate volatility.

Narayan (2020) checked whether shocks to the JPY/USD exchange rate had a permanent or a temporary effect. His hypothesis was that COVID-19 affected the resilience of the exchange rate to shocks. Using a time-varying unit root model, he found that before the pandemic, the yen was non-stationary, but became stationary during the pandemic, which suggests that shocks to the yen had a transitory effect. In another paper, Narayan et al. (2020) showed how exchange rate depreciation increased stock returns during the first year of the COVID-19 pandemic.

The impact of the COVID-19 on the exchange rate of the USD and the CNY was explored by Li et al. (2021), who examined the USD/EUR and the CNY/EUR exchange rates in the period between 22 January 2020 and 7 May 2021. An autoregressive distributed lag model (ARDL) was employed to this end. The results indicate that the total number of daily confirmed COVID-19 cases and COVID-related deaths negatively affected the exchange rates of the Chinese and the US currencies. Applying a similar tool, Villarreal-Samaniego (2020) examined the relationship between the exchange rates of currencies of oil exporting and importing countries and the COVID-19 variables. The estimated models indicated that there was a large dependence between the exchange rates and the COVID-19 variables. Devpura (2021) investigated the link between the EUR/USD exchange rate and oil futures price. It was observed that oil prices affected the above exchange rate, but when controlling for the impact of COVID-19, this relationship disappeared, except for the exchange rate in March 2020.

Other research work on this subject comprise papers that used different testing tools. For example, Pasiouras and Daglis (2020) employed a new Bayesian vector model to test the dependency between the spread of COVID-19 and changes in the exchange rates of currencies. The proposed model revealed the impact of the confirmed cases of COVID-19 on exchange rates that other economic models could not explain. Using a wavelet analysis, Iqbal et al. (2020) discovered a negative correlation between the exchange rate of the Chinese renminbi (yuan) and the number of COVID-19 cases. Also, Sharma et al. (2021) used wavelet coherence to examine the potential associations between the number of the confirmed COVID-19 cases, the average daily temperature, exchange rates, and the stock market returns in 15 countries. The results demonstrated that the COVID-19 cases had significant long-term effects on the exchange rate returns in most of the affected countries.

Studies on correlation networks among major currencies are gaining importance. The structural properties of the foreign exchange market using topological network analysis have been addressed by many researchers, e.g. Cao et al. (2020), Hong and Yoon (2022), Miśkiewicz (2021), Naylor et al. (2007), or Ortega and Matesanz (2006). Ortega and Matesanz (2006), having analysed the exchange rates of 28 currencies in the period of 1990–2002, found out that the leading global currency was the US dollar. Naylor et al. (2007) discovered strong clustering of Southeast Asian currencies during the Southeast Asian crisis.

In most network evolution analyses, correlation was chosen as the preferred metric. However, a good alternative here could be the Dynamic Time Warping (DTW) measure, widely regarded as the best distance measure for time series (Silva et al., 2016). Wang et al. (2012) employed it to investigate the topology of a similarity network between 35 major currencies in the foreign exchange market, using the minimal spanning tree (MST) approach. The analysis was carried out for the period of 2005–2011, which was divided into three sub-periods: before, during and after the US sub-prime crisis. The resulting hierarchical trees allowed the examination of the currency clusters in each sub-period. The results confirmed that the US dollar and the euro were the world's dominant currencies. However, the US dollar was gradually losing its central position, whereas the euro was acting like a stable centre throughout the entire crisis.

Other authors also used MSTs in analysing currency markets, e.g. Górski et al. (2008), Kazemilari and Mohamadi (2018), Limas (2019), Rešovský et al. (2013) and Wang et al. (2013). Gupta and Chatterjee (2020) suggested a new method of studying the evolution of the foreign exchange market topology as the COVID-19 pandemic was spreading. They proposed aligned correlation (AC), which is able to determine more precisely the lead-lag relationship between financial time series. These authors studied 29 countries and observed that as the COVID-19 crisis progressed, all the currencies become strongly interlinked with each other. In addition, the US dollar began to play an even more significant role in the currency market than before.

The purpose of this study is to assess the similarity between the time series of currency exchange rates before and during the COVID-19 crisis. In addition, the study aims to examine the relationship between the exchange rates of currencies and time series for new COVID-19 cases per 1 million inhabitants in selected countries. In other words, the study's goal is to find out in what way exchange rates of different currencies were linked to the observed development of the pandemic. The DTW method was applied to check if the changes in the exchange rates were related to the spread of the COVID-19 pandemic, and if they were, to what extent it was so.

2. Research method

The study is based on data from two sources. The currency exchange rates came from the Stooq website (stooq.com), and the data regarding daily COVID-19 new cases from the Our World in Data website (ourworldindata.org), both accessed on 10 November 2021. Currency data cover the period from 1 January 2019 to 10 November 2021, and the COVID-19 data the period from 1 March 2020 to 10 November 2021.

The period of the analysis was divided into three sub-periods: the pre-COVID-19 sub-period, the first-COVID-19 sub-period, and the second-COVID-19 sub-period. Definitions of sub-periods along with sub-sample sizes are presented in Table 1.

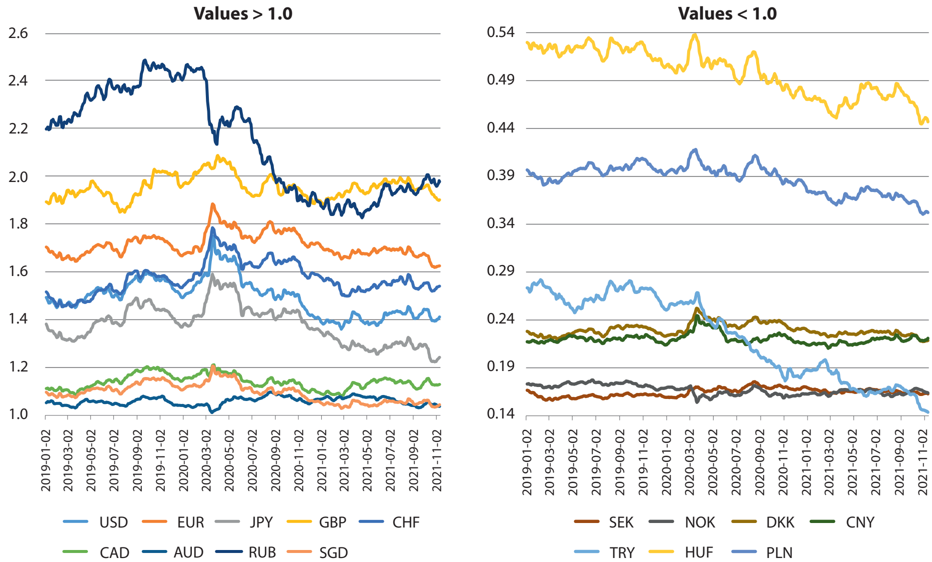
Table 1. Definition of sub-periods with sub-sample sizes

Sub-period	Range of time	Number of observations for	
		currencies	new COVID-19 cases
Pre-COVID-19	from 1.01.2019 to 29.02.2020	298	.
First-COVID-19	from 1.03.2020 to 31.12.2020	217	306
Second-COVID-19	from 1.01.2021 to 10.11.2021	222	314

Source: author's work based on data from the Our World in Data website.

The exchange rates of the following currencies were analysed: the US dollar (USD), the euro (EUR), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Canadian dollar (CAD), the Australian dollar (AUD), the Swedish krona (SEK), the Norwegian krone (NOK), the Danish krone (DKK), the Russian ruble (RUB), the Chinese renminbi (CNY), the Turkish new lira (TRY), the Singapore dollar (SGD), the Czech koruna (CZK), the Hungarian forint (HUF), and the Polish zloty (PLN). All these currencies were denominated in the New Zealand dollar (NZD). The choice of a numeraire is difficult in currency analysis, because currencies are mutually priced and therefore there is no independent numeraire. With no standard solution to this issue, it is gold, less popular currencies (such as the TRY) or special drawing rights (SDRs) that are often taken into consideration. The NZD was chosen as the numeraire following Gupta and Chatterjee (2020), Naylor et al. (2007) and Wang et al. (2012). To mitigate the impact of the possible shocks on currency prices, a 5-day moving average was calculated. Figure 1 presents the time series of exchange rates of the studied currencies except for CZK (as its exchange rate is much higher than the exchange rates of the other currencies), and Table 2 shows the descriptive statistics for the currency exchange rates against the NZD.

Figure 1. Time series for the exchange rates of the studied currencies (except CZK) against the New Zealand dollar



Note. USD – US dollar, EUR – euro, JPY – Japanese yen, GBP – British pound, CHF – Swiss franc, CAD – Canadian dollar, AUD – Australian dollar, SEK – Swedish krona, NOK – Norwegian krone, DKK – Danish krone, RUB – Russian ruble, CNY – Chinese renminbi, TRY – Turkish new lira, SGD – Singapore dollar, CZK – Czech koruna, HUF – Hungarian forint, PLN – Polish zloty. The CZK exchange rate is not included, because it is much higher than the exchange rates of other currencies. 5-day moving average; the vertical axes represent the exchange rates.
Source: author's work based on data from the Stooq website.

Table 2. Descriptive measures for the 17 currency exchange rates against the New Zealand dollar

Currency	Sub-period								
	pre-COVID-19			first-COVID-19			second-COVID-19		
	mean	std. dev.	CV	mean	std. dev.	CV	mean	std. dev.	CV
USD	1.522	0.041	0.027	1.542	0.085	0.055	1.407	0.021	0.015
EUR	1.699	0.030	0.018	1.769	0.039	0.022	1.676	0.020	0.012
JPY	1.395	0.050	0.036	1.451	0.063	0.043	1.289	0.027	0.021
GBP	1.948	0.050	0.026	1.970	0.056	0.028	1.945	0.028	0.014
CHF	1.536	0.050	0.032	1.653	0.048	0.029	1.542	0.021	0.014
CAD	1.148	0.032	0.028	1.145	0.029	0.025	1.126	0.021	0.019
AUD	1.053	0.013	0.012	1.066	0.019	0.017	1.064	0.016	0.015
SEK	0.160	0.002	0.012	0.169	0.002	0.014	0.165	0.002	0.009
NOK	0.172	0.003	0.015	0.163	0.003	0.021	0.165	0.002	0.014
DKK	0.228	0.004	0.017	0.237	0.005	0.021	0.225	0.003	0.012
RUB	2.362	0.084	0.035	2.083	0.144	0.069	1.911	0.048	0.025
CNY	0.220	0.003	0.012	0.224	0.007	0.033	0.218	0.003	0.015
TRY	0.266	0.009	0.034	0.215	0.026	0.120	0.171	0.013	0.075

Table 2. Descriptive measures for the 17 currency exchange rates against the New Zealand dollar (cont.)

Currency	Sub-period								
	pre-COVID-19			first-COVID-19			second-COVID-19		
	mean	std. dev.	CV	mean	std. dev.	CV	mean	std. dev.	CV
SGD	1.115	0.023	0.021	1.116	0.037	0.033	1.050	0.009	0.009
CZK	6.637	0.119	0.018	6.621	0.140	0.021	6.523	0.104	0.016
HUF	0.520	0.009	0.017	0.500	0.016	0.033	0.470	0.011	0.023
PLN	0.396	0.006	0.016	0.395	0.010	0.024	0.368	0.006	0.018

Note. Abbreviations as in Figure 1; std. dev. – standard deviation, CV – coefficient of variation.
Source: author's work based on data from the Stooq website.

More specifically, in Table 2 we can see the descriptive statistics for the pre-COVID-19 sample, the first-COVID-19 sample and the second-COVID-19 sample. The first-COVID-19 sub-period is characterised by a higher coefficient of variation values than the other two sub-periods.

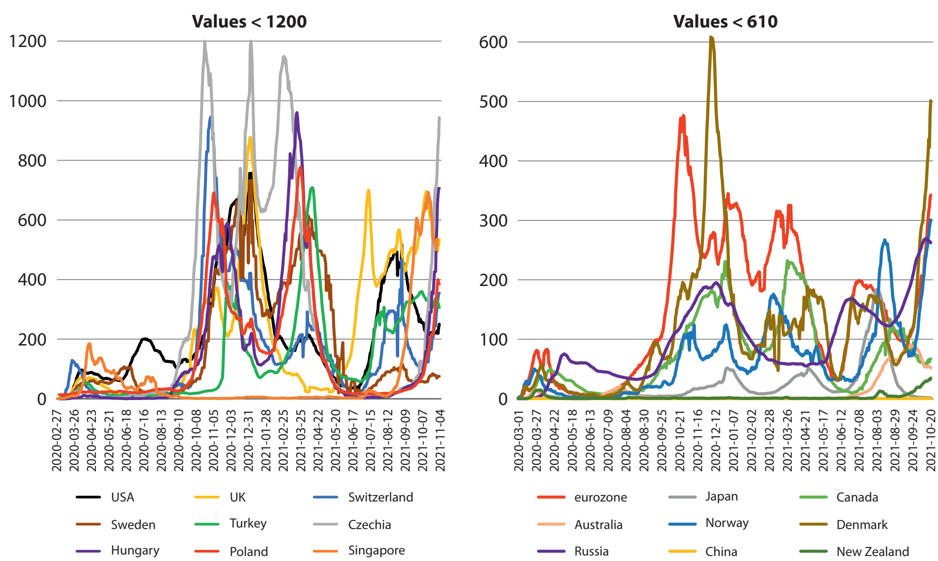
Before the outbreak of the COVID-19 pandemic, there was some discussion about the status of the USD as the world's reserve currency, with many believing that it was losing its dominant position. However, in the time of the pandemic, the dollar proved that it still was the major currency on international currency markets. The first few months of the pandemic caused a return to the dollar in search of security, and it strengthened against almost all currencies. The currencies of emerging markets and commodity exporters (including developed economies such as Australia, Canada or Norway), which experienced particularly sharp depreciation as a result of the collapse in commodity prices, fell the most. The reopening of economies after March 2020 helped reduce the demand for the dollar, as a consequence of which this currency weakened in the period from 23 March to the end of December 2020. More specific reasons for this was China's economy rebounding, the eurozone agreeing on a joint pandemic relief package, and clinical trial results showing the effectiveness of some anti-coronavirus vaccines. At the beginning of 2021, the dollar again started strengthening against many currencies. The key factors affecting the USD are interest rates and the Fed monetary policy, hence the expected hikes in interest rates resulted in the stronger dollar.

The world's second most important currency, the euro, was gradually appreciating against the US dollar from April 2020, but in the early 2021 started depreciating. In the spring of 2020, the spreading pandemic triggered a surge in capital inflows to Switzerland (regarded as a 'safe heaven'), putting pressure on the Swiss franc and causing its appreciation. The Chinese renminbi depreciated slightly against the USD in the first half of 2020, but in the second half of the year appreciated strongly, which was caused by favorable interest rate differentials, positive economic data, and strong trade surpluses.

An important factor influencing exchange rate movements in 2021 was the development of vaccination campaigns in individual countries. Currency markets are sensitive to local economic conditions, with demand favouring countries where the pace of vaccination is relatively fast. It would therefore be interesting to look for links between exchange rates and the number of infected people in each country.

Time series for the new COVID-19 cases per 1 million people in the 18 studied countries or regions (the USA, the eurozone, Japan, the United Kingdom, Switzerland, Canada, Australia, Sweden, Norway, Denmark, Russia, China, Turkey, Singapore, Czechia, Hungary, Poland and New Zealand) are presented in Figure 2. A 7-day moving average for daily COVID-19 cases was calculated to mitigate the effects of under-reporting on weekends or holidays and over-reporting on subsequent days.

Figure 2. Time series for the new COVID-19 cases per 1 million people in the studied countries



Note. 7-day moving average; the vertical axes show the daily counts of COVID-19 cases per 1 million people.
Source: author's work based on data from the Our World in Data website.

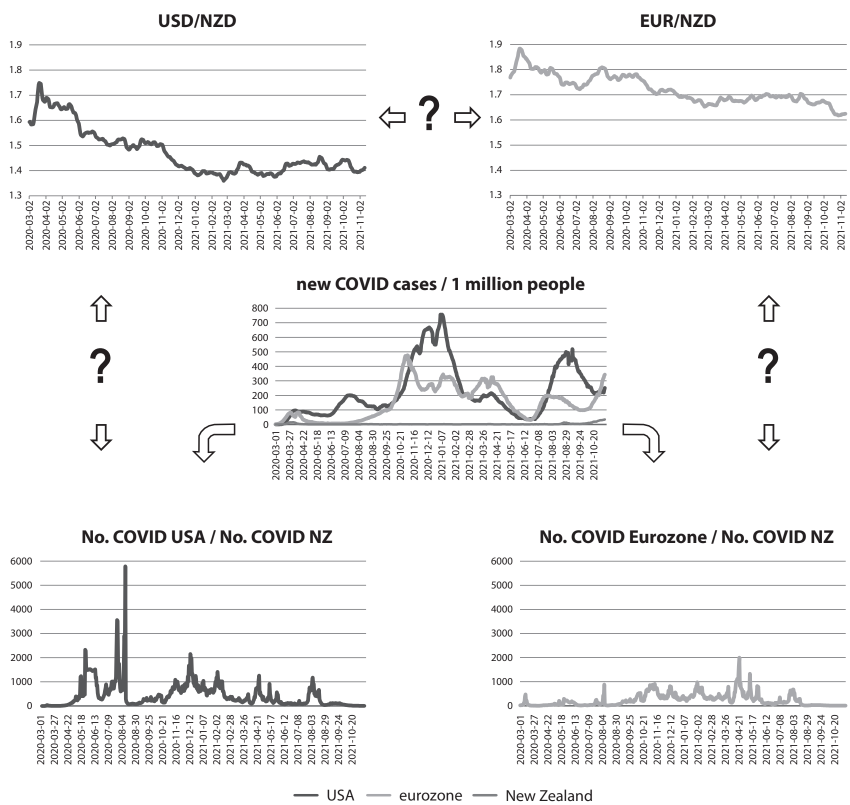
Many countries experienced multiple waves of the coronavirus, with the first one hitting in the spring of 2020, and the subsequent waves operating in different regions of the world for a long time after that.

This study intends to determine the similarity between time series of exchange rates of different currencies in the three sub-periods (Table 1) and to investigate the existence of a relationship between the currency series and the COVID-19 time series. In order to assess such a relationship, attention will be focused on the exchange rate of two currencies against the quotient of the number of the COVID-19 cases in two countries:

$$\text{exchange rate} = \frac{\text{currency of country A}}{\text{currency of country B}} \text{ vs. } \frac{\text{number of COVID-19 cases in country A}}{\text{number of COVID-19 cases in country B}}.$$

More specifically, the USD/NZD exchange rate will be compared with the quotient No._Covid_USA / No._Covid_NZ. The relationships to be explored are presented in Figure 3.

Figure 3. Relationships between currencies and COVID-19 time series



Source: author's work based on data from the Stooq and Our World in Data websites.

As mentioned in the aims of the study, in order to compare time series for currency exchange rates (currency pairs X/NZD), and to check if the spread of

COVID-19 is related to the exchange rates (and if yes, to what extent it is so), the Dynamic Time Warping (DTW) distance method was used. The DTW measure aligns two time series along time, minimising the effects of shifting and distortion by allowing a flexible transformation to detect similar but phase-shifted sequences. It performs non-linearly in the series, stretching or compressing them locally so that one is as similar as possible to the other (Aghabozorgi et al., 2015). The DTW method can be used to compare two time series of different lengths, which is the case in this study, as we are comparing here the exchange rate series and the series related to COVID-19. Their lengths vary, as currency rates are quoted five times a week, and the COVID-19 cases are reported seven times a week.

The DTW was developed by Bellman and Kalaba in the late 1950s (Bellman & Kalaba, 1959) and explored extensively in the 70s by applying it to the speech recognition (cf. Myers & Rabiner, 1981; Rabiner et al., 1978; Sakoe & Chiba, 1978). Currently it is applied in many areas, such as biometrics, e.g. finger print verification, hand writing application (Tappert et al., 1990); computer animation, e.g. gesture recognition (Arici et al., 2014); bioinformatics, e.g. gene expression alignment (Aach & Church, 2001); data mining, e.g. music information retrieval (Müller, 2007); and finance, e.g. statistical arbitrage (Stübinger, 2019).

The DTW similarity measure utilises dynamic programming to find an optimal path between two time series. Suppose there are two numerical sequences $X = (x_1, x_2, \dots, x_N)$ and $Y = (y_1, y_2, \dots, y_M)$. The length of the two sequences might be different. In order to make meaningful comparisons between them, they must be normalised (Łuczak, 2018). The DTW algorithm starts with local distances calculation between the elements of the two sequences. That results in the local cost matrix with the following elements:

$$c_{ij} = c\left(x_i, y_j\right) = |x_i - y_j|, \quad i = 1, 2, \dots, N, \quad j = 1, 2, \dots, M. \tag{1}$$

The task of an optimal alignment between series X and Y involves ordering all sequence points by minimising the overall cost, which is done by means of the dynamic programming algorithm. Once the local cost matrix is built, the algorithm searches for an alignment path that passes through the low-cost areas – the 'valleys', and avoids the 'mountains' of high cost (Stübinger & Schneider, 2020).

Formally, the alignment (warping) path is a sequence $p = (p_1, \dots, p_L)$, with $p_l = (n_l, m_l) \in \{1, \dots, N\} \times \{1, \dots, M\}$ for $l \in \{1, \dots, L\}$ ($L \in \{\max(N, M), \dots, N + M - 1\}$),which must satisfy the boundary, the monotonicity, and the continuity conditions (Keogh & Ratanamahatana, 2005). The boundary condition ensures that the starting and ending points of the warping path are the first and the last points of the aligned time series. The monotonicity condition maintains the temporal ordering of points (the path never returns), and the continuity condition prevents the warping path from long jumps, i.e. $p_{l+1} - p_l \in \{(1,0),(0,1),(1,1)\}$ for $i = 1, \dots, L-1$.

The cost function associated with the warping path which measures the overall cost associated with the alignment has the following form:

$$c_p(X,Y) = \sum_{l=1}^{L} c(x_{n_l}, y_{m_l}). \tag{2}$$

The optimal warping path has the minimal cost associated with the alignment. The optimal match between X and Y is then:

$$DTW(X,Y) = c_{p^*}(X,Y) = \min\{c_p(X,Y) \big| p \in P\}, \tag{3}$$

where P is the set of all possible warping paths.

The DTW method finds the optimal path p^* iteratively, using a dynamic programming algorithm. It builds the global cost matrix **D**, which is defined as below:

$$\mathbf{D}(1,m) = \sum_{k=1}^{m} c(x_1, y_k) \quad \text{for } m = 1, \dots, M, \tag{4}$$

$$\mathbf{D}(n,1) = \sum_{k=1}^{n} c(x_k, y_1) \quad \text{for } n = 1, \dots, N, \tag{5}$$

$$\begin{gathered}\mathbf{D}(n,m) = c(x_n, y_m) + \min\{\mathbf{D}(n-1,m), \mathbf{D}(n,m-1), \mathbf{D}(n-1,m-1)\} \\ \text{for } 1 < n \le N, 1 < m \le M.\end{gathered} \tag{6}$$

Once the global cost matrix **D** is built, the DTW distance is given by $DTW(X,Y) = \mathbf{D}(N,M)$, and the optimal warping path p^* can be found by simply backtracking from the point (N,M) to the $(1,1)$. The optimal path is identified on the basis of the neighbour with the minimum value. The shapes of the warping curves provide information about the pairwise correspondence of time points (e.g. if p^* is above diagonal, then the time series X leads Y).

The DTW yields optimal solution in the $O(MN)$ time, which could be further improved through different techniques. The fast DTW, proposed by Salvador and Chan (2007), uses a multilevel approach and is able to find an accurate warping path in linear time. The work of Silva et al. (2016) investigates the effects of relaxing various constraints on the DTW measure.

The distance between the analysed time series for currencies and the ratios between the numbers of infected people in two countries was calculated by means of the DTW. The DTW distance allowed currencies to be grouped according to their change before and during the pandemic, and their relationship with the pandemic dynamics to be examined. The calculated distances can be directly applied to the classification (Sardá-Espinosa, 2019). After measuring the similarities between the time series, agglomerative hierarchical clustering was performed. To carry out a hierarchical cluster tree, a single link with the squared Euclidean distance was used. In this study, the Silhouette, the Dunn and the Calinski-Harabasz indices were applied for assessing the goodness of clustering.

3. Results of the study

In this section, the DTW measure is used to analyse the evolution of the currency market as the COVID-19 pandemic was spreading. For each of the three pre-defined sub-periods, the analysis was conducted in the following steps:

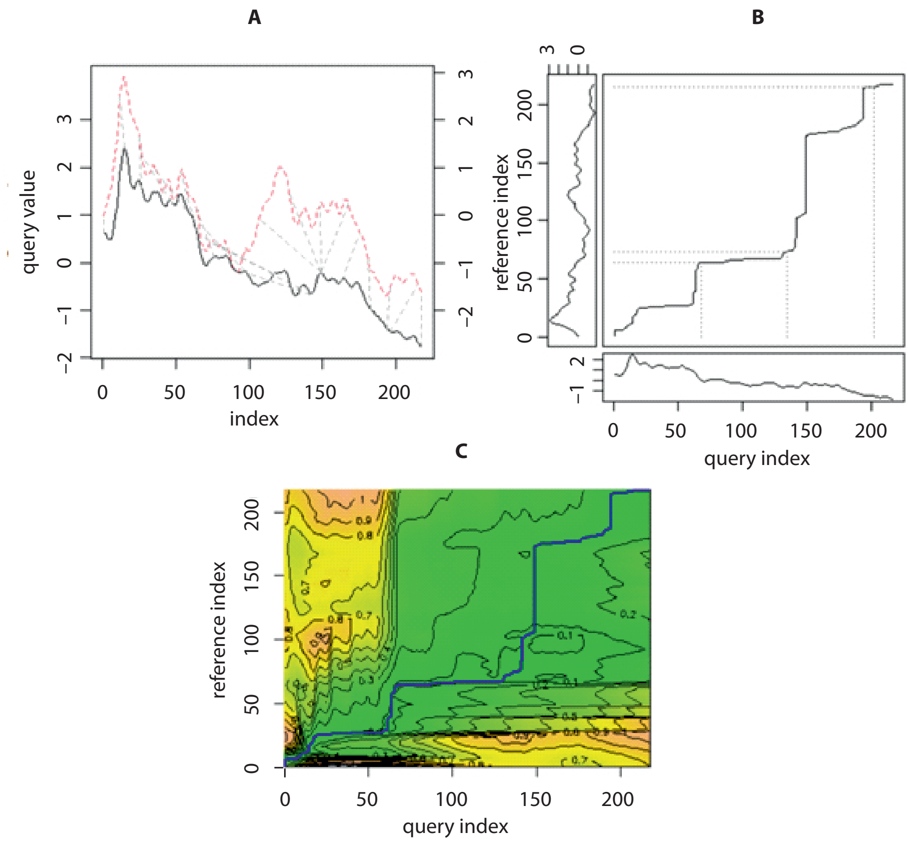
- the time series for currency exchange rates were standardised;
- the DTW distance between all time series was calculated;
- based on the distance matrix, the hierarchical clustering of the currency exchange rates was performed using a single link with the squared Euclidean distance. The goodness of clustering was checked by means of the Silhouette, the Dunn and the Calinski-Harabasz indices.

Additionally, for the first-COVID-19 sub-sample and the second-COVID-19 sub-sample, the following procedure was adopted:

- the time series for the currency exchange rates and the quotients of the number of COVID-19 cases in two countries were standardised;
- the DTW distance between the time series for currency exchange rates and the quotients of the number of COVID-19 cases was calculated;
- the obtained results were compared with the results of the hierarchical clustering of the currency exchange rates.

For illustrative purposes, Figure 4 presents the output of the DTW algorithm for two currency exchange rates: the USD/NZD and the EUR/NZD, in the first-COVID-19 sub-period.

Figure 4. Alignment between time series for the USD/NZD and the EUR/NZD exchnage rates in the first-COVID-19 sub-period

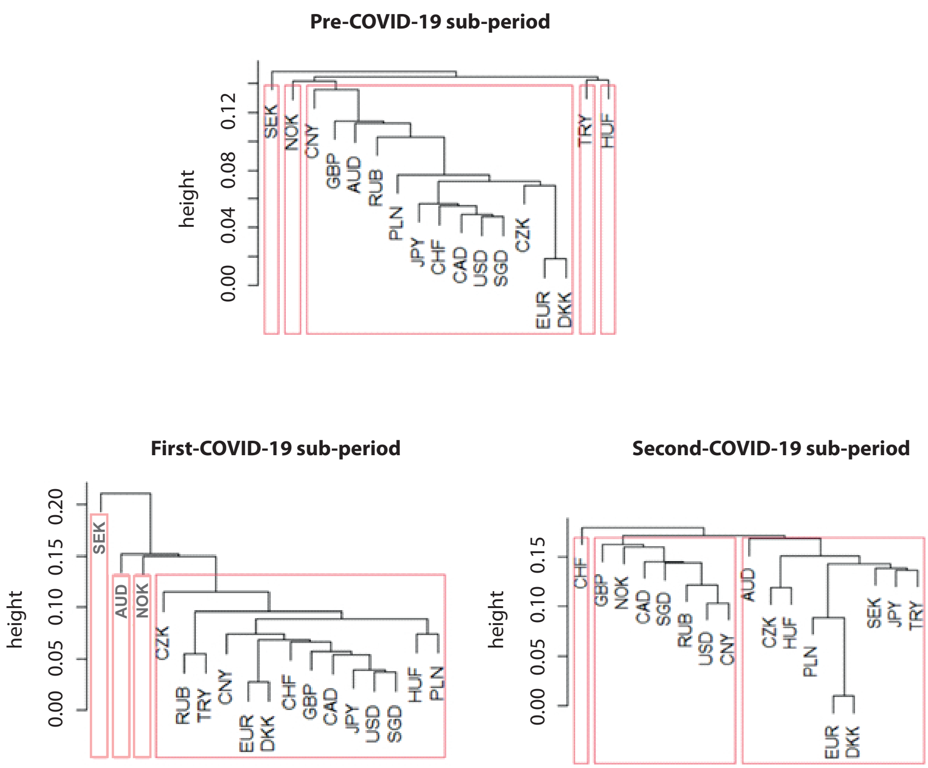


Note. A – time series graphs with alignment (black solid line – USD/NZD, scale on the left; red dashed line – EUR/NZD, scale on the right; grey dashed lines – time series alignment); B – three-way plot of the time series alignment (query indices for USD/NZD, reference indices for EUR/NZD, vertical axes of graphs on the left and at the bottom – standardised time series values); C – local costs and the optimal warping path for the alignment. Regions of low and high cost are marked green and red, respectively.
Source: author's work based on data from the Stooq website.

Figure 4A shows the values of the studied time series for the USD/NZD and the EUR/NZD with the performed alignments, computed using the dtw package for R (Giorgino, 2009). Figure 4B is a visual representation of the optimal warping paths corresponding to Figure 4A. The shape of the warping curve provides information about the pairwise correspondence of time points. In this case, the identified optimal warping path was mostly below the diagonal, i.e. the time series for the EUR/NZD led the time series for the USD/NZD. Figure 4C illustrates the local costs and the identified optimal warping path p^* given the proper time series. Graphically, the sequence of points p^* runs along a 'valley' of low cost, and avoids 'mountains' of high cost.

The hierarchical clustering of the currency exchange rates was performed for the pre-COVID-19 sub-period, the first-COVID-19 sub-period and the second-COVID-19 sub-period on the basis of a distance matrix for all currencies (Figure 5).

Figure 5. Cluster dendrograms of currencies in different COVID-19 sub-periods



Note. Abbreviations as in Figure 1.
Source: author's work based on data from the Stooq website.

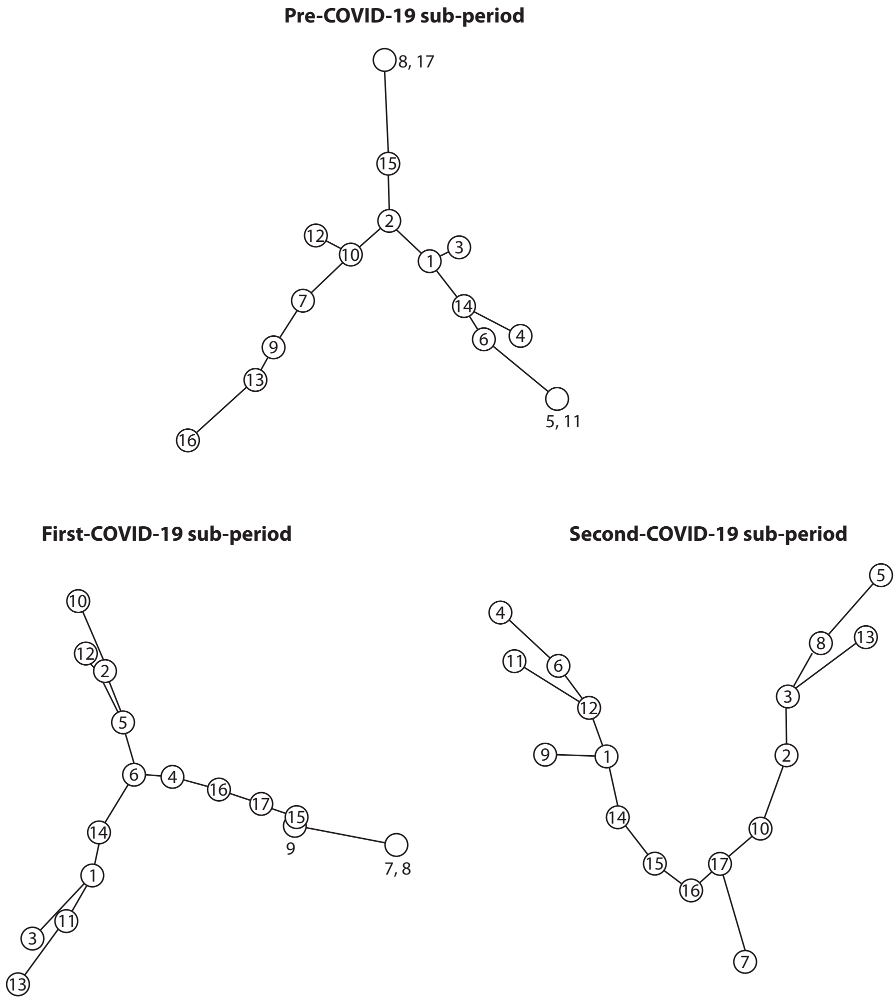
Based on the dendrogram for the pre-COVID-19 sub-period, five clusters of currency exchange rates were distinguished, with the USD, SGD, CAD, CHF, JPY, EUR, DKK, PLN, RUB, AUD, GBP, CZK and the CNY forming the first big one. It can be assumed, following Ortega and Matesanz (2006), that in the pre-pandemic period, the leading currency in the world was the USD. The remaining four currencies – the SEK, NOK, TRY and the HUF formed separate single-element clusters. While deciding on the number of groups, first the value of the Silhouette index and then the other two indices were taken into consideration, although the value of the Silhouette index (less than 0.3) indicated a weak group structure. The SEK, NOK and the HUF showed low volatility during the pre-COVID-19 sub-period. In addition, the HUF depreciated strongly. The volatility of the currencies in the large cluster was high and these currencies often strengthened against the NZD.

For the first-COVID-19 sub-period, four clusters were formed: a large one (the USD, SGD, JPY, CAD, GBP, CHF, EUR, DKK, CNY, HUF, PLN, RUB, TRY and the CZK), and three single-element clusters for the SEK, AUD and the NOK. The value of the Silhouette index (0.511) indicated that a reasonable structure was found. The outbreak of the pandemic resulted in group tendencies for the development of exchange rates. The NOK and the AUD weakened greatly after the pandemic began, but then started to strengthen until the autumn of 2020. The SEK, however, strengthened only against the NZD. Other currencies (especially the USD, JPY, SGD and the CHF) saw a significant rise in their exchange rates with the onset of the pandemic, and then slowly depreciated as economies opened up (although the EUR and the DKK were appreciating towards the end of the year). Since in our analysis all currency rates are expressed against the NZD, the obtained result might also indicate the reaction of this currency to the pandemic. It should be noted here that the obtained result does not contradict the finding of Gupta and Chatterjee (2020), who argued that with the outbreak of the COVID-19 crisis, all currencies became strongly linked to each other, and the USD played a central role in the foreign exchange market.

In the second-COVID-19 sub-period (2021), three clusters of currencies were distinguished. All the three indices pointed to this solution, however the observed group structure was weak (the Silhouette index was about 0.25). Two large clusters and one single-element cluster were observed. The behavior of the CHF/NZD exchange rate, which was stable in 2021, was an exception. The exchange rates of the USD, CNY, RUB, SGD, CAD, NOK and the GBP against the NZD all shaped in a similar way: they strongly appreciated in 2021. The EUR, DKK, PLN, CZK, HUF, SEK, JPY, TRY and the AUD, which formed the last group, behaved in a different way. This group contained the EUR, JPY and the TRY, which were depreciating in 2021. Such a result was similar to that obtained by Wang et al. (2012), who analysed the effects of the US sub-prime crisis. Its consequence was that the USD was gradually losing its position of a stable centre, which was eventually overtaken by the EUR.

To compare the changes which took place in the currency markets before and after the outbreak of the COVID-19 pandemic, minimal spanning trees were built on the basis of the estimated DTW distances (Figure 6).

Figure 6. Minimum spanning tree representations obtained using the DTW distance between currencies in different phases of the COVID-19 pandemic

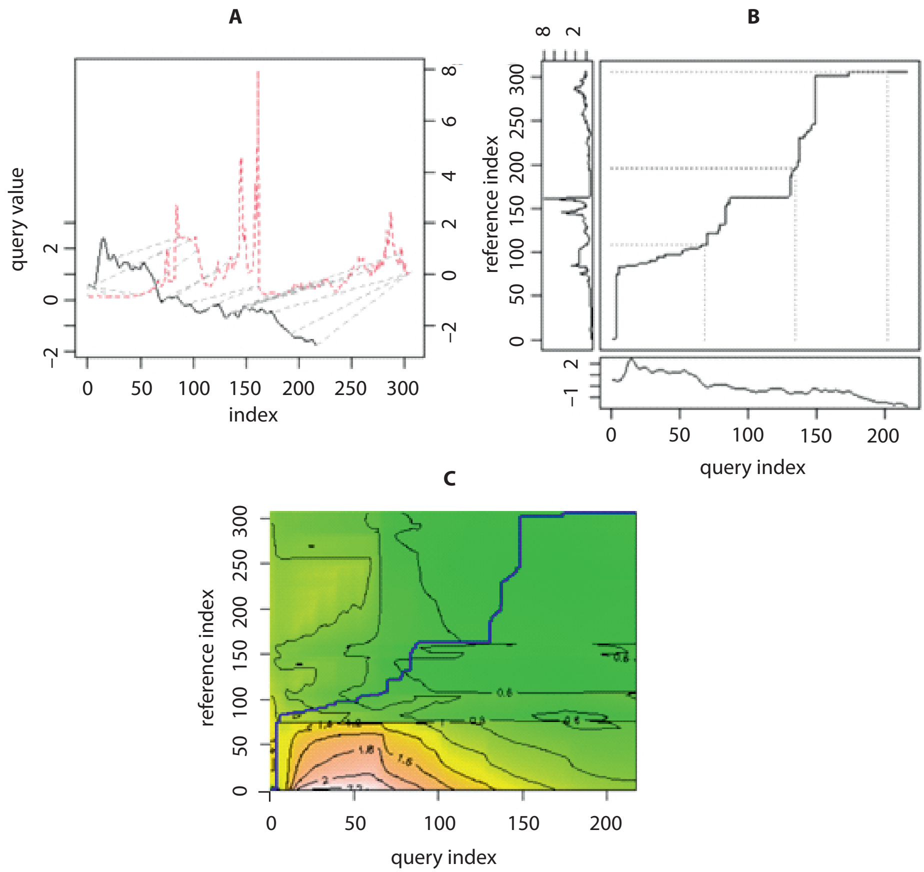


Note. 1 – USD, 2 – EUR, 3 – JPY, 4 – GBP, 5 – CHF, 6 – CAD, 7 – AUD, 8 – SEK, 9 – NOK, 10 – DKK, 11 – RUB, 12 – CNY, 13 – TRY, 14 – SGD, 15 – CZK, 16 – HUF, 17 – PLN; abbreviations as in Figure 1.
Source: author's work.

The obtained results confirm that before the pandemic, the main currencies in the world concentrated around a pair of two 'similar' ones – the EUR and the USD. However, in the later period of the pandemic, particularly in 2021, the foreign exchange market polarised and currencies turned either to the USD or to the EUR.

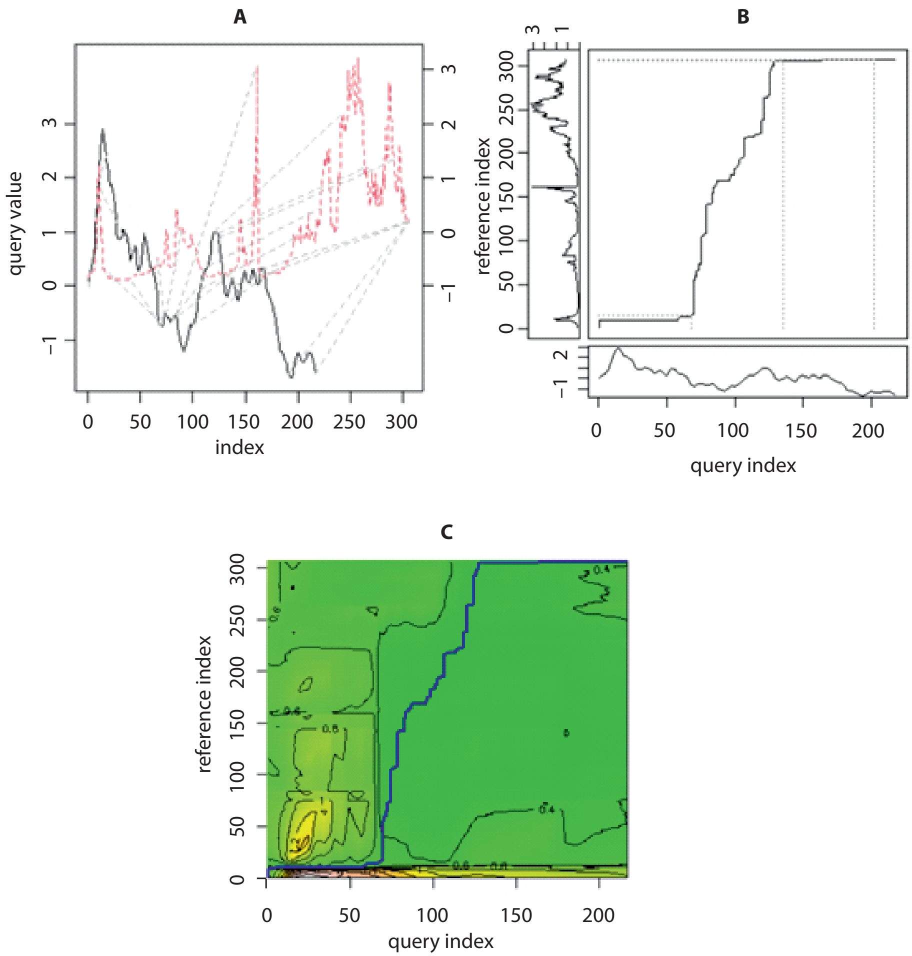
In the next step, the DTW distance between the time series for exchange rates and the quotients of the number of COVID-19 cases were calculated. Figure 7 illustrates the alignment performed by the DTW algorithm between the USD/NZD exchange rate and the time series for the quotient of the number of COVID-19 cases in the USA and New Zealand in the first-COVID-19 sub-period. Figure 8, on the other hand, shows the relationship between the EUR/NZD exchange rate and the time series for the quotient of the number of COVID-19 cases in the eurozone and New Zealand.

Figure 7. Alignment between time series for the USD/NZD exchange rate and the quotient of the number of COVID-19 cases in the USA and New Zealand in the first-COVID-19 sub-period



Note. A – time series graphs with alignment (black solid line – the USD/NZD exchange rate, scale on the left; red dashed line – No._Covid_USA / No._Covid_NZ, scale on the right; grey dashed lines – time series alignment); B – three-way plot of the time series alignment (query indices for the USD/NZD exchange rate, reference indices for the No._Covid_USA / No._Covid_NZ, vertical axes of graphs on the left and at the bottom – standardised time series values); C – local costs and the optimal warping path for the alignment. Regions of low and high costs are marked in green and red, respectively.
Source: author's work based on data from the Stooq and Our World in Data websites.

Figure 8. Alignment between time series for the EUR/NZD exchange rate and the quotient of the number of COVID-19 cases in the eurozone and New Zealand in the first-COVID-19 sub-period



Note. A – time series graphs with alignment (black solid line – the EUR/NZD exchange rate, scale on the left; red dashed line – No._Covid_eurozone / No._Covid_NZ, scale on the right; grey dashed lines – the time series alignment); B – three-way plot of the time series alignment (query indices for the EUR/NZD exchange rate, reference indices for the No. Covid_eurozone / No._Covid_NZ, vertical axes of graphs on the left and at the bottom – standardised time series values); C – local costs and the optimal warping path for the alignment. Regions of low and high costs are marked in green and red, respectively.
Source: author's work based on data from the Stooq and Our World in Data websites.

It is worth noting that for the USD, the identified optimal warping path was above the diagonal, i.e. the time series for the USD/NZD led the time series for the quotient of the number of COVID-19 cases in the USA and New Zealand. However, at the time of the unexpected outbreak of the pandemic, the optimal warping path for the EUR was below the diagonal, i.e. the time series for the quotient of the number of

COVID-19 cases in the eurozone and New Zealand led the time series for the EUR/NZD. Apparently, the European currency was affected by the pandemic to a larger extent than the USD, which seemed to have been affected more by external factors.

In the last step, the obtained distances for the X/NZD time series pairs vs. the quotient of the number of the COVID-19 cases in country X and New Zealand (Table 3) were compared with the results of the hierarchical clustering of exchange rates (Figure 5).

Table 3. DTW distance values for pairs of time series: X/NZD vs. No._Covid_X/No._Covid_NZ

Currency	DTW	Currency	DTW
First-COVID-19 sub-period		**Second-COVID-19 sub-period**	
SEK	0.227	HUF	0.211
AUD	0.233	PLN	0.230
CNY	0.283	DKK	0.240
NOK	0.307	CHF	0.241
SGD	0.342	SEK	0.244
EUR	0.390	EUR	0.254
CHF	0.408	SGD	0.256
CZK	0.425	CZK	0.321
PLN	0.426	NOK	0.325
DKK	0.434	JPY	0.346
HUF	0.494	CAD	0.382
JPY	0.500	AUD	0.399
CAD	0.513	GBP	0.399
RUB	0.538	USD	0.413
USD	0.549	CNY	0.442
GBP	0.689	TRY	0.443
TRY	0.732	RUB	0.626

Note. Abbreviations as in Figure 1; distances for currencies belonging to the same clusters (presented by dendrograms in Figure 5) are marked with the same colours.
Source: author's work based on data from the Stooq and Our World in Data websites.

In the first-COVID-19 sub-period, four clusters were identified: a large one and three single-element clusters. The distances with COVID-19 quotients for the currencies belonging to them are marked in Table 3 with distinct colours. The isolated currencies (the SEK, AUD and the NOK) were characterised by a small distance from the COVID-19 cases quotient in the respective countries. This may indicate a stronger sensitivity of the exchange rates of these currencies to the development of the pandemic during its first year.

The second-COVID-19 sub-period, covering the year 2021, split currencies into three clusters. This time currencies of European countries (the EUR, CHF, DKK, HUF, PLN, SEK and the CZK) were more strongly linked to the development of the pandemic. In contrast, the trajectories of major global currencies such as the USD, GBP, CNY and the RUB were significantly far from the examined time series associated with the number of the infected. This indicated lower sensitivity of these currencies to the pandemic, as economies continued to revive and global trade relations began to normalise. In particular, the world's major currency, the USD, was treated as a 'safe haven' reserve currency, and its exchange rate was influenced by many other factors not directly related to the evolution of the number of the COVID-19 infections. To sum up, as regards the two major world currencies, the EUR exchange rate seemed to have been more closely related to the course of the pandemic than the USD exchange rate, which seemed to have been priced without a significant relation to the dynamics of COVID-19.

4. Conclusions

It is obvious that factors such as economic growth, international trade conditions, interest rates and other economic variables affect exchange rates, but it is still possible to conduct a simple comparative analysis of exchange rate trajectories of different currencies and juxtapose them with time series which characterise the development of the pandemic. As mentioned before, this was the objective of this study. However, a more thorough assessment of the changes entailed by the pandemic necessitated the application of more sophisticated statistical and econometric techniques.

The obtained results showed that the foreign exchange markets had varying structures throughout the three studied periods (before the pandemic, in the year of the outbreak of the pandemic, and in its later course). The outbreak of COVID-19 led to a concentration of most currencies around the USD. However, after the economies revived, a polarisation of the currency market occurred, with the world's major currencies clustering either around the USD or the EUR. It became evident that the EUR exchange rate was largely dependent on the course of the pandemic in particular countries, while the USD seemed to have been valued regardless of the dynamics of the pandemic.

The findings of the study offer other significant practical applications. The economic and financial costs of the COVID-19 pandemic affected both the institutional and individual participants of the economy. From the investment point of view, the results reveal the presence of links between the number of the COVID-19 cases and the foreign exchange market, thus proving that portfolio managers need to take into account the risks associated with the spread of the illness while making decisions. The observed relationship between the COVID-19 outbreak and currency prices indicates that the uncertainty associated with the pandemic was diminishing as international trade and economic sectors such as tourism and the hospitality industry slowly returned to their normal functioning.

In the planned follow-up to this research, the authors intend to investigate the significance of the results obtained applying different clustering algorithms and using a currency other than the NZD as a reference.

References

Aach, J., & Church, G. M. (2001). Aligning gene expression time series with time warping algorithms. *Bioinformatics*, *17*(6), 495–508. https://doi.org/10.1093/bioinformatics/17.6.495.

Aghabozorgi, S., Shirkhorshidi, A. S., & Wah, T. Y. (2015). Time-series clustering – A decade review. *Information Systems*, *53*, 16–38. https://doi.org/10.1016/j.is.2015.04.007.

Arici, T., Celebi, S., Aydin, A. S., & Temiz, T. T. (2014). Robust gesture recognition using feature pre-processing and weighted dynamic time warping. *Multimedia Tools and Applications*, *72*(3), 3045–3062. https://doi.org/10.1007/s11042-013-1591-9.

Bellman, R., & Kalaba, R. (1959). On adaptive control processes. *IRE Transactions on Automatic Control*, *4*(2), 1–9. https://doi.org/10.1109/TAC.1959.1104847.

Cao, H., Guo, Z., Li, Y., & Ran, Z. (2020). The Relationship Structure of Global Exchange Rate Based on Network Analysis. *Journal of Mathematical Finance*, *10*(1), 58–76. https://doi.org/10.4236/jmf.2020.101006.

Devpura, N. (2021). Effect of COVID-19 on the relationship between Euro/USD exchange rate and oil price. *MethodsX*, *8*, 1–8. https://doi.org/10.1016/j.mex.2021.101262.

Feng, G.-F., Yang, H.-C., Gong, Q., & Chang, C.-P. (2021). What is the exchange rate volatility response to COVID-19 and government interventions? *Economic Analysis and Policy*, *69*, 705–719. https://doi.org/10.1016/j.eap.2021.01.018.

Giorgino, T. (2009). Computing and Visualizing Dynamic Time Warping Alignments in R: The dtw Package. *Journal of Statistical Software*, *31*(7), 1–24. https://doi.org/10.18637/jss.v031.i07.

Górski, A. Z., Drożdż, S., Kwapień, J., & Oświęcimka, P. (2008). Minimal Spanning Tree graphs and power like scaling in FOREX networks. *Acta Physica Polonica A*, *114*(3), 531–538. https://doi.org/10.48550/ARXIV.0809.0437.

Gupta, K., & Chatterjee, N. (2020). *Examining Lead-Lag Relationships In-Depth, With Focus On FX Market As Covid-19 Crises Unfolds*. https://arxiv.org/ftp/arxiv/papers/2004/2004.10560.pdf.

Hong, M. Y., & Yoon, J. W. (2022). The impact of COVID-19 on cryptocurrency markets: A network analysis based on mutual information. *PLoS ONE*, *17*(2), 1–24. https://doi.org/10.1371/journal.pone.0259869.

Iqbal, N., Fareed, Z., Shahzad, F., He, X., Shahzad, U., & Lina, M. (2020). The nexus between COVID-19, temperature and exchange rate in Wuhan city: New findings from partial and multiple wavelet coherence. *Science of The Total Environment*, *729*, 1–9. https://doi.org/10.1016/j.scitotenv.2020.138916.

Iyke, B. N. (2020). The Disease Outbreak Channel of Exchange Rate Return Predictability: Evidence from COVID-19. *Emerging Markets Finance and Trade*, *56*(10), 2277–2297. https://doi.org/10.1080/1540496X.2020.1784718.

Kazemilari, M., & Mohamadi, A. (2018). Topological Network Analysis Based on Dissimilarity Measure of Multivariate Time Series Evolution in the Subprime Crisis. *International Journal of Financial Studies*, *6*(2), 1–16. https://doi.org/10.3390/ijfs6020047.

Keogh, E., & Ratanamahatana, C. A. (2005). Exact indexing of dynamic time warping. *Knowledge and Information Systems*, *7*(3), 358–386. https://doi.org/10.1007/s10115-004-0154-9.

Li, C., Su, Z.-W., Yaqoob, T., & Sajid, Y. (2021). COVID-19 and currency market: a comparative analysis of exchange rate movement in China and USA during pandemic. *Economic Research – Ekonomska Istraživanja*. https://doi.org/10.1080/1331677X.2021.1959368.

Limas, E. (2019). An application of minimal spanning trees and hierarchical trees to the study of Latin American exchange rates. *Journal of Dynamics and Games*, *6*(2), 131–148. https://doi.org/10.3934/jdg.2019010.

Łuczak, M. (2018). Combining raw and normalized data in multivariate time series classification with dynamic time warping. *Journal of Intelligent and Fuzzy Systems*, *34*(1), 373–380. https://doi.org/10.3233/JIFS-171393.

Miśkiewicz, J. (2021). Network Analysis of Cross-Correlations on Forex Market during Crises. Globalisation on Forex Market. *Entropy*, *23*(3), 1–19. https://doi.org/10.3390/e23030352.

Müller, M. (2007). *Information Retrieval for Music and Motion*. Springer-Verlag. https://doi.org/10.1007/978-3-540-74048-3.

Myers, C. S., & Rabiner, L. R. (1981). A comparative study of several dynamic time-warping algorithms for connected word recognition. *The Bell System Technical Journal*, *60*(7), 1389–1409. https://doi.org/10.1002/j.1538-7305.1981.tb00272.x.

Narayan, P. K. (2020). Has COVID-19 Changed Exchange Rate Resistance to Shocks?. *Asian Economics Letters*, *1*(1), 1–4. https://doi.org/10.46557/001c.17389.

Narayan, P. K., Devpura, N., & Wang, H. (2020). Japanese currency and stock market – What happened during the COVID-19 pandemic?. *Economic Analysis and Policy*, *68*, 191–198. https://doi.org/10.1016/j.eap.2020.09.014.

Naylor, M. J., Rose, L. C., & Moyle, B. J. (2007). Topology of foreign exchange markets using hierarchical structure methods. *Physica A: Statistical Mechanics and its Applications*, *382*(1), 199–208. https://doi.org/10.1016/j.physa.2007.02.019.

Ortega, G. J., & Matesanz, D. (2006). Cross-country hierarchical structure and currency crises. *International Journal of Modern Physics C*, *17*(3), 333–341. https://doi.org/10.1142/S012918310600856X.

Pasiouras, A., & Daglis, T. (2020). The dollar exchange rates in the Covid-19 era: Evidence from 5 currencies. *European Research Studies Journal*, *23*(2), 352–361. https://doi.org/10.35808/ersj/1828.

Rabiner, L., Rosenberg, A., & Levinson, S. (1978). Considerations in dynamic time warping algorithms for discrete word recognition. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, *26*(6), 575–582. https://doi.org/10.1109/tassp.1978.1163164.

Rešovský, M., Horváth, D., Gazda, V., & Siničáková, M. (2013). Minimum Spanning Tree Application in the Currency Market. *Biatec*, *21*(7), 21–23. https://www.nbs.sk/_img/Documents/_PUBLIK_NBS_FSR/Biatec/Rok2013/07-2013/05_biatec13-7_resovsky_EN.pdf.

Sakoe, H., & Chiba, S. (1978). Dynamic programming algorithm optimization for spoken word recognition. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, *26*(1), 43–49. https://doi.org/10.1109/tassp.1978.1163055.

Salvador, S., & Chan, P. (2007). FastDTW: Toward Accurate Dynamic Time Warping in Linear Time and Space. *Intelligent Data Analysis*, *11*(5), 70–80. https://doi.org/10.3233/IDA-2007-11508.

Sardá-Espinosa, A. (2019). Time-series clustering in R using the dtwclust package. *R Journal*, *11*(1), 22–43. https://doi.org/10.32614/RJ-2019-023.

Sharma, G. D., Tiwari, A. K., Jain, M., Yadav, A., & Erkut, B. (2021). Unconditional and conditional analysis between Covid-19 cases, temperature, exchange rate and stock markets using wavelet coherence and wavelet partial coherence approaches. *Heliyon*, *7*(2), 1–30. https://doi.org/10.1016/j.heliyon.2021.e06181.

Silva, D. F., Batista, G. E. A. P. A., & Keogh, E. (2016). *On the effect of endpoints on dynamic time warping* (SIGKDD Workshop on Mining and Learning from Time Series, II). https://core.ac.uk/download/pdf/78275924.pdf.

Stübinger, J. (2019). Statistical arbitrage with optimal causal paths on high-frequency data of the S&P 500. *Quantitative Finance*, *19*(6), 921–935. https://doi.org/10.1080/14697688.2018.1537503.

Stübinger, J., & Schneider, L. (2020). Epidemiology of coronavirus COVID-19: Forecasting the future incidence in different countries. *Healthcare*, *8*(2), 1–15. https://doi.org/10.3390/healthcare8020099.

Tappert, C. C., Suen, C. Y., & Wakahara, T. (1990). The state of the art in online handwriting recognition. Pattern Analysis and Machine Intelligence. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *12*(8), 787–808. https://doi.org/10.1109/34.57669.

Villarreal-Samaniego, D. (2020). *COVID-19, Oil Prices, and Exchange Rates: A Five-Currency Examination*. http://dx.doi.org/10.2139/ssrn.3593753.

Wang, G.-J., Xie, C., Han, F., & Sun, B. (2012). Similarity measure and topology evolution of foreign exchange markets using dynamic time warping method: Evidence from minimal spanning tree. *Physica A: Statistical Mechanics and its Applications*, *391*(16), 4136–4146. https://doi.org/10.1016/j.physa.2012.03.036.

Wang, G.-J., Xie, C., Chen, Y.-J., & Chen, S. (2013). Statistical Properties of the Foreign Exchange Network at Different Time Scales: Evidence from Detrended Cross-Correlation Coefficient and Minimum Spanning Tree. *Entropy*, *15*(5), 1643–1662. https://doi.org/10.3390/e15051643.