The relationship between the COVID-19 pandemic and the currency exchange rates: evidence through dynamic time warping method

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GOAL

The Covid-19 pandemic has affected the entire economic system. Currency exchange rates are also affected by the current crisis.

The objective is to assess the similarity between the time series of currency exchange rates and the Covid-19 time series.

E.g., we investigate the relationship between the EUR/USD exchange rate and the ratio of Covid-19 daily cases in Eurozone and USA).

We will observe how the Covid-19 spread has influenced the exchange rates by employing the dynamic time warping (DTW) method.

DATA SOURCES

1. https://ourworldindata.org/coronavirus-source-data: the number of new Covid cases per million in Eurozone, USA, UK, Switzerland, Japan, China, Canada, Australia, Norway, Sweden, Poland from April 1, 2020, to June 21, 2021 (n=313) [for further analysis we calculate the ratios of Covid-19 daily cases for two territories]
2. https://stooq.pl/: the currency exchange rates for EUR, USD, GBP, CHF, JPY, CNY, CAD, AUD, NOK, SEK, PLN from April 1, 2020, to June 21, 2021 (n=444)

PROCEDURE

STEP 1 NORMALIZATION

In order to make meaningful comparisons between two time series, both must be normalized (we use a standard method – *z*-normalization).

STEP 2 DYNAMIC TIME WARPING (DTW)

DTW distance method is used to compare time series of different lengths.

It allows an adjustment of the time axis to find similar but phase-shifted sequences.

Invented by Bellman and Kalaba, was developed for dealing with speech recognition problems. It has been further used in the field of music information retrieval, for gesture recognition, in bioinformatics, in finance, for labour market analyses etc.

$X = (x_1, x_2, \dots, x_N)$ and $Y = (y, y_2, \dots, y_M)$ – two time series

The local cost measure for X and Y: $c(x_i, y_j) = |x_i - y_j|, i = 1, \dots, N, j = 1, \dots, M$.

We will find the optimal alignment between X and Y having minimal overall cost. Such a point-to-point alignment between X and Y can be represented by a time warping path, which 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 $l \in \{1, \dots, L\}$ $(L \in \{\max(N, M), \dots, N + M - 1\})$, satisfying the boundary, monotonicity and step size conditions. Every index from the time series X must be matched with one or more indices from the time series Y.

The optimal warping path is denoted by the match that has the minimal total cost:

$\mathrm{DTW}(X, Y) = c_{p*}(X, Y) = \min\{c_p(X, Y) | p \in P\}$

The optimal path p^* could be found using a dynamic programming algorithm, building the accumulated cost matrix D in the following way:

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

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

$$D(n, m) = c(x_n, y_m) + \min\{D(n-1, m), D(n, m-1), D(n-1, m-1)\}$$

$$\text{for } 1 < n \leq N, 1 < m \leq M$$

The minimal distance between time series X and Y is:

$$\mathrm{DTW}(X, Y) = D(N, M).$$

STEP 3 HIERARCHICAL CLUSTERING

The calculated DTW distances have an application in hierarchical clustering.

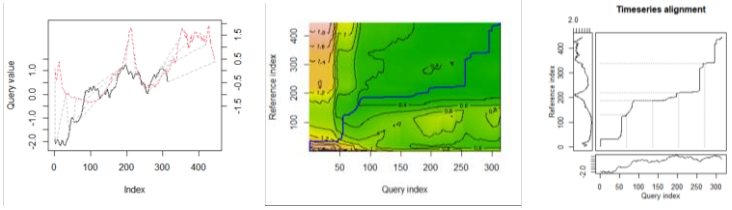
After measuring the similarities between the time series, we perform the agglomerative hierarchical clustering.

The 1 Nearest-Neighbour (1-NN) method with the squared Euclidean distance is used.

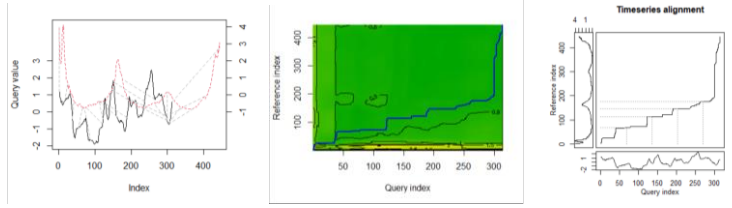
RESULTS

SELECTED RESULTS OF STEP 2

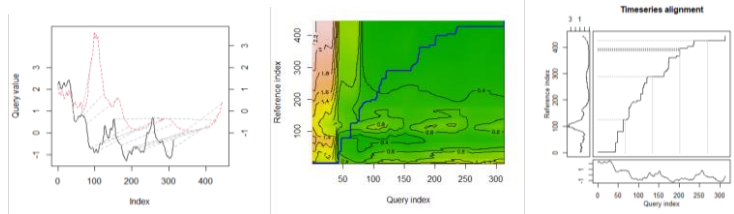
EUR/USD vs. nrCovid_Eurozone/nrCovid_USA:



EUR/PLN vs. nrCovid_Eurozone/nrCovid_Poland:



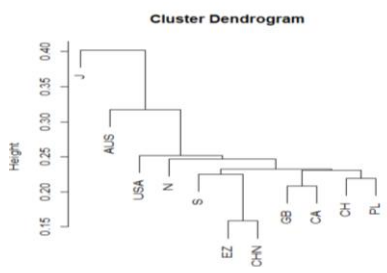
USD/PLN vs. nrCovid_USA/nrCovid_Poland:



DTW distance matrix:

	EZ	USA	GB	CH	J	CHN	CA	AUS	N	S
USA	0.2518256									
GB	0.2323221	0.3870438								
CH	0.4077924	0.2586520	0.3002927							
J	0.6328635	0.4021023	0.5900513	0.5342211						
CHN	0.1584089	0.4830490	0.3297285	0.2854486	0.7092157					
CA	0.3122238	0.3551029	0.2080892	0.3174489	0.6909906	0.2598498				
AUS	0.5733206	0.6212196	0.4310987	0.5271880	0.7256626	0.3658434	0.5318434			
N	0.2865013	0.3914748	0.2655982	0.3490291	0.5150051	0.2521437	0.2465751	0.3176470		
S	0.3155215	0.3779185	0.3464324	0.3320700	0.5682717	0.2249333	0.2726338	0.3852551	0.2540349	
PL	0.2789118	0.2574415	0.2436943	0.2190531	0.4243483	0.2784712	0.2304782	0.5502322	0.3402307	0.4205059

RESULT OF STEP 3



CONCLUSIONS

1. Using the DTW measure the distance between analyzed time series was calculated. The calculated distance allowed to group currencies according to their change caused by the pandemic.
2. It was found that some currency exchange rates were strongly associated with the development of the pandemic (e.g., EUR/CNY, GBP/CAD, CHF/PLN), others less (for JPY, AUD).

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