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Differences in Capital Market Network Structures under COVID-19

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Abstract. This paper analyses the structural changes of the underlying stock and currency markets as well as the industrial productions by using a minimum spanning tree graph on a Central and East European sample. The aim is to point out the similarities and differences of the COVID-19 pandemic compared to previous recessions, namely the Dot-com crisis in the early 2000s and the Subprime crisis around 2008. Focusing on the incidence, closeness, and betweenness properties of the graph, we are looking for the emergence of a shock-propagating hub. We identify such a hub during the Subprime crisis but not during the COVID-19 pandemic, which points to the higher efficiency of the economic policy to absorb the worst effects of the crisis.

Keywords: COVID-19, network, minimum spanning tree graph, CEE

JEL Classification: C31, C33, D53, E58

1. Introduction

Countries had to face a series of widespread lockdowns during the COVID-19 pandemic, generating a technical recession globally. Meanwhile, the Eurozone was already in a state of slow growth one year before this crisis, creating a chance for a “perfect storm”. This paper focuses on the differences of the COVID-19 crisis observed by comparing its impacts on the stock markets, currencies, and industrial production on a Central and East European sample – in the light of the previous crisis periods (namely the Dot-com bubble in the early 2000s and the Subprime crisis of 2008). This special attention was motivated by the nature of the crisis: unlike the previous recessions, it was not triggered by a financial crisis, and both the unconventional monetary and fiscal policies seemed to be more prepared to absorb its effects. The composition of the group of countries was motivated by the strong economic connections of Czechia, Croatia, Hungary, Poland, and Romania with the European Union (and especially with the Eurozone) both from funding and foreign trade perspectives (Balla, 2014). Therefore, they seemed to be an ideal test group to see how the shocks propagated amongst them.

Our research is looking for the signs of contagion, assuming that in this case we can identify one country (or the Eurozone) that finds itself in the middle of a cross-country network. Therefore, we will employ a minimum spanning tree graph on the entire timeframe and on the different recession subsets as well to look for such an emergent behaviour. In case of the appearance of such a hub, we can assume that the market is in a hyper-synchronized state and shock propagation is present. Otherwise, the market is dominated much more by the country-specific issues and not by the abruptly changing market sentiment.

This study is structured as follows: Section 2 summarizes the foundations of the network theory concept, and then the stock and currency market implications are underlined in the theoretical background section to point out the importance of the usage of minimum spanning tree graphs during crisis analysis. This is followed by the data and methods in Section 3, where the analysed datasets are determined and the Student-t copula framework is introduced, which is a crucial ingredient for the graph analysis. The development of the datasets and the influence of recession periods are presented in Section 4. Section 5 summarizes the different graph metrics to determine the market topology under the different datasets and time periods.

2. Theoretical Background

2.1 Contagions and Networks

Contagion has a broad and narrow definition.[1] The general one is that it is the cross-border transmission of shocks or general cross-border spillovers that need not be associated with shocks, while the restrictive definition means that the correlations between countries in "crisis times" compared to "tranquil times" have relatively increased.[2] This indicates the spread of shocks from one (or a group of) market(s) or country/ies to other(s) (Pritsker, 2001). Contagion spreads between countries through three basic links: financial, real, and political. Financial links are

1 See: http://go.worldbank.org/JIBDRK3YC0.

2 Interdependence exists when there is no significant difference between the correlations in extreme and normal conditions, but these can still be high.

the links of the international financial system such as joint financial institutions, interconnected lenders, non-bank financial market participants, etc. The actual connections relate to international trade or the cross-border division of labour driven by FDI. Political ties are based on mutual exchange rate agreements, as well as other ongoing remittances based on international cooperation.

Transmission-related extreme events emerge from the dynamics of the underlying system, as Jentsch et al. (2006) stated, meaning that the initial shock and the market topology also determine the development of domino effects on the capital market due to the sudden increase of partner risk (Benedek et al., 2007). Partner risk became a significant systemic factor in the post-Breton Woods era due to the unavoidable role of financial innovations in risk management, or even in the essential maturity transformation in the banking sector (Barrel et al., 2010). It is important to understand the systemic background of the market because the allowance of free capital movement in the last three decades has increased the cross-market correlations since the 1980s (Obstfeld and Taylor, 2002). Heathcote and Perry (2004) underlined that capital markets integrated faster than the real economies in the recent 30 years – despite that macro fundamentals tended to move together, showing a "real regionalization" between 1972 and 1986, while "financial regionalization" emerged later with higher geographic diversification, cross-border consumption, and the increasing volatility of external trade. Goetzman et al. (2005) pointed out the following paradox: diversification strategies were efficient only before the liberalization of capital flows because convertibility allows the spreading of risks. Cross-market correlation was high also in the past when world economy was integrated: both between 1875 and 1914 and since 1972 – which is parallel to the results of Chen and Zhang (1997) and Obstfeld and Taylor (2002).

To model the market network (*n*), it is necessary to define the interactions (*c*) between the nodes or actors (*a*) on the market, which determines the shape (*sh*) of the entire network. If extreme events emerge from the underlying system, then the following formula has to collect the most important factors behind these dynamics:

$$n(a, c, sh)$$

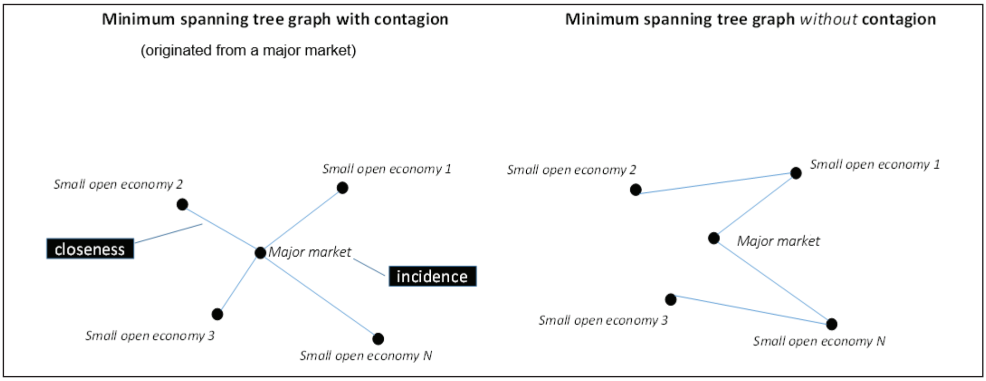
Before the comparison of the efficient market and complex market models, it is necessary to define the basic characteristics necessary for describing a network. Market participants as nodes (actors) differ from each other only in the number of connections in the basic network theory. Therefore, the *sh* shape of the network can be described with five structural properties: average path length (*pa*), clustering coefficient (*cl*), degree distribution (*dd*), small-world effect (*sw*), *and* connectivity (*cy*) (Barabási and Albert, 1999; Wang and Chen, 2003; Watts and Strogatz, 1998; Alderson, 2008).

$$sh(pa, cl, dd, sw, dy)$$

The *distribution of degrees* describes the heterogeneity and the hierarchy between the nodes. The total number of links among *i* nodes is called *degree* k_i, which represents its importance in the network. The average degree of the network is *k*, the average of k_i over all *i*-s. The node degree distribution function *P(k)* is the probability that a randomly selected node has exactly *k* edges. *Average path length* is calculated by taking the average distance pa_{ij} between the i^{th} and j^{th} nodes of the network. The *clustering coefficient* is the average proportion of a node's neighbour pairs that are also neighbours to each other: *cl* as the average of cl_i over all *i*-s. The *small-world effect* can occur due to the interaction between the clustering coefficient and the grade distribution. Shortcuts reduce the distance between nodes if there are nodes (hubs) in the network with degrees above average; they allow the *small-world effect* to be present. *Hubs* are usually responsible for synchronizing the network. *Connectivity* represents the durability of the connections between nodes: its high level indicates a rapid recombination of the nodes, while the low level indicates stability. These properties can be developed with more variables, for example with different kind of connections, as Csermely (2008) contends: the so-called "weak" connections represent the informal while the "strong" connections the contractual relations between the nodes. Also, we can distinguish between the actors (nodes) on the capital markets not only by the number of their connections – representing this partner's importance on systemic level –, but we can check the fragile nature of their parameters too (see Benedek et al., 2007).

This paper focuses on the emergence of the topological changes among the economic actors under market stress. Therefore, we will assume that network topology will become much more hub-based (or centralized) under stress – not just for the actors *within* but also for those *between* the markets. It means that we would like to identify the emerging clustering behaviour on the macro-level, focusing only on the stock and currency market and the industrial production, hoping that cross-border investments, borrowing, and production will be visible on the shape of minimum spanning tree graphs (*Figure 1*).

A system is complex if the outcomes are highly irregular and seemingly unpredictable despite the potential simplicity of the equation of its motion (Kantz et al., 2006: 71). Capital market complexity causes collective effects under extreme trading days, as Bonanno et al. (2001) suggest, resulting in contagion, divergence, and interdependence as well. The assumed price equilibrium represents the fundamental value of an asset – a significant change in the cross-market correlation points to the possibility of exogenous divergence between fundamental and market value on extreme trading days. Market bubbles can emerge on a market with rational actors, but the upper "coincidence" is crucial because trade activity is affected both by trading patterns and cognitive factors (Komáromi, 2006: 76). Therefore, the description of capital markets as complex networks requires the assumption of the bounded rationality of the actor as well (Herrmann and Pillath, 2000). The complex or even the scale-free network can describe the oligopolistic nature of the market, where key market actors are symbolized with the hubs as well as their importance with attached preferences. Statistic phenomena as fat tailness, heteroscedasticity, autocorrelation, or even collective effects are the results of this market structure. Scale-free complex networks are based on the preferential attachments, causing a hub-based structure, as postulated by Barabási and Albert (1999). This structure is between the two extreme statuses, i.e. regular (lattice) and random networks (Watts and Strogatz, 1998).



Source: author's edition

Figure 1. *Minimum spanning tree graph with and without contagions*

The *incidence* of the graph describes the number of connections from one node (in our case country) to another, as *betweenness* represents the degree to which nodes stand between each other, while *closeness* describes the strength of this relation. In a minimum spanning tree design, we can assume that only the most significant edges (node-to-node connections) are represented, so an emerging hub structure can prove the highly synchronized state of contagions. Under a fully stressed global contagion scenario, we can expect for the emergence of a single hub market, which synchronizes the rest of the network due to crisis propagation. This hub will have a high incidence and betweenness value due to its relative importance in the network, while it will have a strong connection to the rest of the nodes. However, in the case of country-specific stress, the network remains in an atomized (or non-centralized) state, so we will be unable to identify such a node with asymmetric properties.

2.2 Pricing Anomalies

Funding and market liquidity conditions are determined by the secondary market's depth for the assets, as well as the market sentiment (Varga, 2016; BIS, 2011).

Stock market pricing reacts both to the monetary policy instruments and to the expectations of the private sector regarding the future development of the most important macroeconomic indicators as a forward-looking reference (Kurov, 2010; Sági, 2018). Therefore, asset price bubbles can be interpreted as a structural uncertainty in the valuation process, namely about the cash-flow-generating ability or the discount rate (Robinson and Stone, 2004). A tighter monetary policy can help to disinflate such bubbles by setting the discount rate, but it can increase the volatility of asset prices if it "leans against the wind" (Galí, 2013). Monetary policy can have, therefore, an endogenous influence on asset valuation.

Currencies, however, are special assets since they represent both the external and the internal balances of two economies, wherefore they can be considered as more appropriate indicators for cross-country shock propagation. Their values are affected by the change in the demand for individual currencies, which can be biased by the "fear of floating" phenomenon, as Calvo and Reinhart (2002) showed. It means that central banks are following a flexible regime that pursues undeclared exchange rate target (*de jure* floating) – but neither the adversary effects of devaluation-driven inflation or debt revaluation nor the appreciation-driven pressure on productivity is preferred to be minimized. In case a powerful shock affects the economy, a long period of exchange rate fluctuations can follow, which can be harmful for the tradable sector. However, crisis periods can trigger the investments and capital flow towards safe assets and "safe-haven" currencies with a dramatic price effect (Ranaldo and Söderlind, 2009). This can lead to deflationary waves in an open economy like Switzerland or Czechia, where temporary currency ceilings had to be implemented in the mid-2010s (Madaras and Györfy, 2016).

3. Data and Methods

In this research, we used monthly dataset from February 2000 to September 2020 to capture contagions among a set of Central-East European (Czech, Croatian, Hungarian, Polish, and Romanian) stock markets, currencies, and industrial output against their counterparts in the Eurozone. To represent the financial links, stock and currency markets were analysed. For the stock markets, this paper used Euro-Stoxx (Eurozone), PX (Czechia), CROBEX (Croatia), BUX (Hungary), WIG (Poland), and BET (Romania), while currencies were denominated in US dollars (USD) in the same order: EUR/USD, CZK/USD, HRK/USD, HUF/USD, PLN/USD, RON/USD. All these data were acquired from the *Refinitiv Eikon* database. Meanwhile, real links were captured through the industrial output from the Euro area 19, Czechia, Croatia, Hungary, Poland, and Romania, downloaded from the Eurostat database.

To compare the different recession periods, we used the Business Cycle Clock of the European Commission, which can be implemented as an official conjuncture dating database. Therefore, the following recession periods were compared: the Dot-com (Oct. 2000–Sept. 2003), the Subprime (Jan. 2008–Sept. 2009), and the COVID-19 (Oct. 2017–Sept. 2020).

We applied minimum spanning tree graphs, which were based on Student-t copulas. To describe Student-t copulas following Bouyé et al. (2000), let us take N number of $X_1,\ldots, X_N$ random variables, whose dependency can be written by the C common or F multivariate distribution:

$$F(x_1, \ldots,\ x_N) = P[F_1(X_1) \leq F_1(x_1), \ldots, F_N(X_N) \leq F(x_N)] = C(F_1(x_1), \ldots F_N(x_N)).$$

With $\rho = \begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix}$ linear correlation matrix and ν degree of freedom, a $T_{\rho,\nu}$

Student's t distribution can be parameterized as:

$$C(x_1, \ldots, x_n, \ldots, x_N; \rho) = |\rho|^{-\frac{1}{2}} \frac{\Gamma\left(\frac{\nu+N}{2}\right)\left[\Gamma\left(\frac{\nu}{2}\right)\right]^N}{\left[\Gamma\left(\frac{\nu+1}{2}\right)\right]^N \Gamma\left(\frac{\nu}{2}\right)} \frac{\left(1+\frac{1}{\nu}\varsigma^T\rho^{-1}\varsigma\right)^{-\frac{\nu+N}{2}}}{\prod_{n=1}^{N}\left(1+\frac{\varsigma_n^2}{\nu}\right)^{-\frac{\nu+1}{2}}}$$

(where $\varsigma_n = t_\nu^{-1}$, $\Gamma(\mathrm{n}) = (\mathrm{n}-1)!$).

Minimum spanning tree graphs were calculated, following the work of Deeley (2020) in Matlab, by imputing the cross-country correlations from the Student-t copula and determining the incidence and closeness variables by this algorithm.

4. Results and Discussion

Currencies in the sample have a long tendency of strong common movements (see Stavárek, 2009), while stock markets have a mild correlation that intensifies under stressed periods (see Kiss, 2017). Meanwhile, the industrial production should be interlinked due to the intense foreign trade among the countries and the high importance of FDI-driven export. Recessions in the Eurozone had a widespread effect on the sample (*Appendix 1*), causing decline in stock market indices and industrial production as well as depreciating currencies. This result means that the recession periods were well calibrated since they were able to capture stressed periods well.

4.1 Stock Markets

Central and East European stock markets (*Table 1*) were characterized by the dominance of the Eurozone during the entire time set, where the Euro-Stoxx index was literally sitting in the middle of the network and dominating corporate valuation. However, we were able to find Euro-Stoxx in a similar central role under the Subprime crisis only when higher closeness ratios were present in the network. The Czech PX and the Hungarian BUX indices had secondary importance at this time, which is interesting since they had a central role during the Dot-com crisis (but with lower overall closeness levels) and the Czech PX had a central role during the COVID-19 period. This result underlines that the COVID-19 recession has had no global impact on public companies' valuation yet and has remained to be a country-specific phenomenon.

Table 1. *Stock market minimum spanning tree graph characteristics*

Entire dataset			
	Incidence	**Closeness**	**Betweenness**
Eurozone	5	0.2454	10
Czechia	1	0.1422	0
Hungary	1	0.1410	0
Poland	1	0.1469	0
Romania	1	0.1281	0
Croatia	1	0.1259	0
Dot-com			
	Incidence	**Closeness**	**Betweenness**
Eurozone	1	0.1190	0
Czechia	2	0.1609	6
Hungary	3	0.1609	7
Poland	1	0.1095	0
Romania	1	0.0789	0
Croatia	2	0.1278	4
Subprime			
	Incidence	**Closeness**	**Betweenness**
Eurozone	3	0.3113	7
Czechia	2	0.3113	6
Hungary	2	0.2505	4
Poland	1	0.2182	0
Romania	1	0.2128	0
Croatia	1	0.1636	0
COVID-19			
	Incidence	**Closeness**	**Betweenness**
Eurozone	2	0.1786	4
Czechia	3	0.2236	8
Hungary	1	0.1215	0
Poland	1	0.1559	0
Romania	1	0.1107	0
Croatia	2	0.1699	4

Source: authors' calculations in Matlab following Deeley (2020)

4.2 Currencies

Currencies were less centralized (*Table 2*), which is a surprising result if we consider their strong correlations. Both the Czech koruna and the euro had a central role in the network with the Hungarian forint in the third position on the entire timeframe. However, we can identify strange differences between the COVID-19 and the previous recession periods: closeness levels increased dramatically, suggesting that the previous slowdown and the following pandemic had an icy grip on all the regional currencies. Meanwhile, we were unable to identify clear hubs, nor the primary role of the euro.

Table 2. *Currency minimum spanning tree graph characteristics*

	Entire dataset		
	Incidence	**Closeness**	**Betweenness**
Eurozone	2	0.2569	6
Czechia	3	0.2569	7
Hungary	2	0.2000	4
Poland	1	0.1386	0
Romania	1	0.1603	0
Croatia	1	0.1899	0
Dot-com			
	Incidence	**Closeness**	**Betweenness**
Eurozone	2	0.2202	6
Czechia	3	0.2202	7
Hungary	2	0.1794	4
Poland	1	0.1106	0
Romania	1	0.1232	0
Croatia	1	0.1523	0
Subprime			
	Incidence	**Closeness**	**Betweenness**
Eurozone	2	0.2051	4
Czechia	2	0.2560	6
Hungary	1	0.1540	0
Poland	1	0.1363	0
Romania	2	0.2560	6
Croatia	2	0.2230	4
COVID-19			
	Incidence	**Closeness**	**Betweenness**
Eurozone	2	0.4067	6
Czechia	1	0.2945	0
Hungary	1	0.2227	0
Poland	2	0.3239	4
Romania	3	0.4067	7
Croatia	1	0.2774	0

Source: authors' calculations in Matlab following Deeley (2020)

4.3 Industrial production

Industrial production (*Table 3*) presented the lowest closeness numbers, which is strange because of the dominance of FDI-driven trade in the region. The central role of Polish industrial production seems to be counter-intuitive as well since most of the countries' foreign trade is conducted with other EU Member States. However, we were able to identify the hub-like behaviour of the Eurozone (probably as a main domain of shocks) during the Subprime crisis, which was a clear example for a systemic crisis both in the financial sector and in the real economy. Fortunately, neither the Dot-com nor the COVID-19 recessions had similar characteristics since they remained to be country-specific phenomena.

Table 3. *Industrial production minimum spanning tree graph characteristics*

	Entire dataset		
	Incidence	**Closeness**	**Betweenness**
Eurozone	1	0.0801	0
Czechia	2	0.1214	4
Hungary	1	0.0972	0
Poland	4	0.1598	9
Romania	1	0.0932	0
Croatia	1	0.0941	0
Dot-com			
	Incidence	**Closeness**	**Betweenness**
Eurozone	2	0.1100	6
Czechia	2	0.0903	4
Hungary	2	0.0913	4
Poland	2	0.1100	6
Romania	1	0.0610	0
Croatia	1	0.0650	0
Subprime			
	Incidence	**Closeness**	**Betweenness**
Eurozone	3	0.1603	7
Czechia	3	0.1603	7
Hungary	1	0.1005	0
Poland	1	0.1079	0
Romania	1	0.0987	0
Croatia	1	0.0908	0
COVID-19			
	Incidence	**Closeness**	**Betweenness**
Eurozone	1	0.0955	0
Czechia	3	0.1576	7
Hungary	2	0.1576	6

Entire dataset			
	Incidence	**Closeness**	**Betweenness**
Poland	2	0.1300	4
Romania	1	0.1011	0
Croatia	1	0.0874	0

Source: authors' calculations in Matlab following Deeley (2020)

5. Conclusions

Despite the disruptive effects of the COVID-19 pandemic on the global value production chains, financial markets remained relatively insulated from its effects, and the situation did not turn into another global financial crisis like the Subprime crisis of 2008. It was mostly averted by the various fiscal and unconventional monetary stimulus packages developed during the 2010s to mitigate the effect of the last global recession and to reinforce the single currency.

This paper pointed out that the financial (stock or currency markets) and the real economy (industrial production) suffered from a global crisis, but the global crisis was not propagated through a hub-like structure this time. However, Central and East European currencies had a dramatically stronger interlinkage, pointing to the systemic nature of the drastic depreciations in 2020. The capital market impact of these periods of economic downturn has been examined in several recent studies (Onofrei et al., 2019; Cărăuşu et al., 2018; Armeanu et al., 2016), whose results are almost consistent with our findings that market contagions are common in this region due to the close interconnectedness of the sample countries. The novelty of this study is based on our methodological approach, because we cannot find any other paper in this topic using Student-t copulas and minimum spanning tree methods.

However, the pandemic is not over yet since most of the European countries are still under some sort of lockdown, production chains are suffering from various bottlenecks due to unstable supply, and the intra-continental passenger transport is frozen. But at least the sovereign risks were not present on the markets, or currencies were able to maintain their automatic stabilizer functions.

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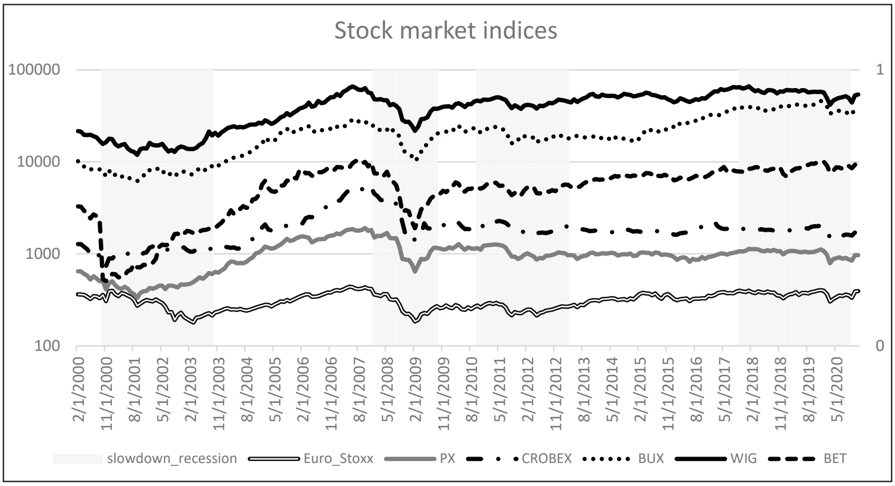
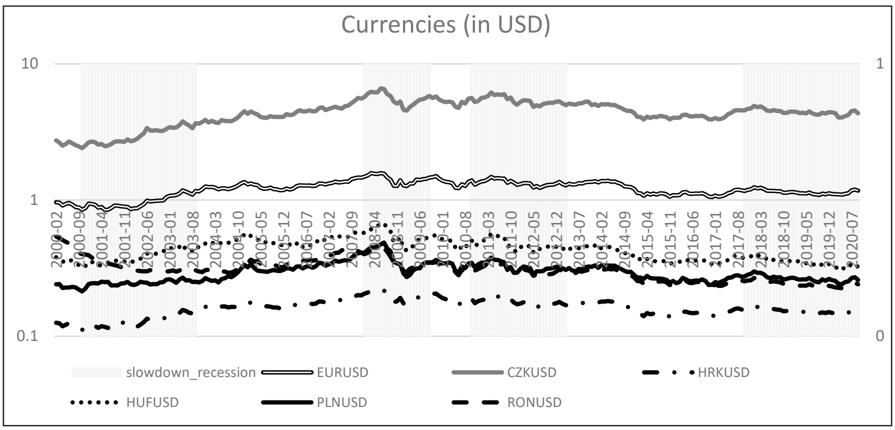
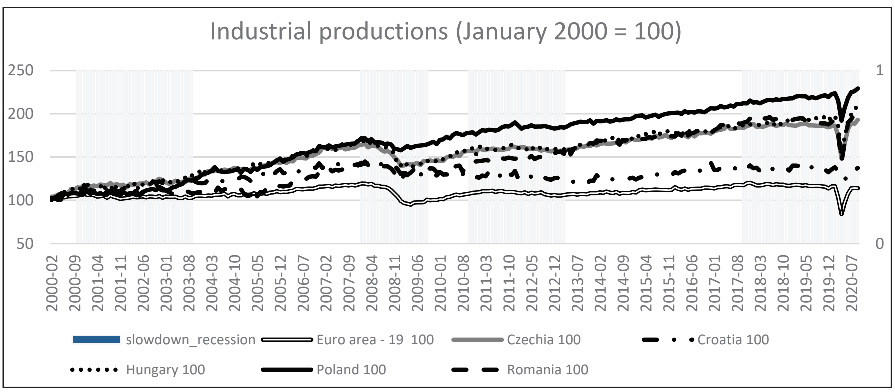
Appendix 1. *Historical values of stock market indices, exchange rates, and industrial productions*







Source: Refinitiv Eikon, Eurostat, European Commission