SPILLOVER INDEX FOR THE EUROPEAN BUSINESS CYCLE

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Abstract

The Covid-19 pandemic has had a significant impact on the international economy. The paper analyses the interdependence between the business cycles of the European Union economies to capture the effect of the Covid-19 pandemic on them.

Using cluster analysis on the monthly data of industrial production indices, two blocks of savings were identified within the European economy. In the second step with the help of an, a contagion index was estimated with a Vector Autoregressive model for the last 10 years.

The results indicate a rapid response, transmitted by contagion, between European economies, leading to a change in the business cycles. The less developed economies absorbed the shocks asymmetrically generated by pandemics amid structural economic problems, which were pre-existing in these economies, thus allowing for a rapid expansion of economic shocks.

Keywords: Covid-19, spillover index, business cycle, European Union, VAR, dendrogram

JEL codes: F44; F42; C32

Introduction

The degree of connection (interdependence) is a central concept in risk management, with practical applications in risk measurement, modern risk management market, credit, and systemic counterparty risk (Diebold and Yilmaz, 2014). The most the well-known method of modeling the degree of connection is correlation analysis, which is valid if and only if the interdependencies are linear.

The dynamics of financial crises is governed by the speed and intensity of spillovers, by the existence of multiple channels of transmission of economic shocks that lead to a non-linear amplification of them. Financial instruments, such as hedging ones, may transmit the financial losses to other institutions. In this case, the contagion is transmitted through prices, so that when prices fall, companies have to sell their assets at a high discount or can no longer sell them. This affects both their balance but also limits their lending.

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In a scenario of economic instability, banks reduce their lending activity, deleverage their portfolio, and thus have a significant impact on the business cycle. The economic expectations are important in the transmission mechanism, so a crisis occurring in one economy / economic area changes the investment expectations for other economies and/or economic zones.

The Asian financial crisis (1997-1998) and the global financial crisis (2007-2009) occurred against the background of a globalized economy that allowed the rapid transmission of economic shocks. The economic and financial links between economies are complex networks, which are not yet well described. In the literature were proposed different families of models that capture, describe, and forecast some of the interconnections between economies.

The transmission of economic shocks has inertia that depends on the affected economic sector, but also the sensitivity of other economic sectors to it. Therefore, a spillover index for the economic cycle is an early warning tool on the economic stress and vulnerabilities that are to occur.

In the current context dominated by the pandemic caused by the Covid-19 virus, the analysis of economic shocks, their origin, and impact dominate both public and academic debates. This article presents a spillover index built on the production indices, which shows the speed of spread of the contagion.

The first part of the paper presents a review of the scientific literature on the contagion of financial markets, the second part presents the methodology of the paper, namely cluster analysis and the Vector Autoregressive model, while in the third part we present the results followed by conclusions in the last part.

2. Literature review

From an economic point of view, Allan and Gale (2012) define contagion as a result coming out from the transmission of an unexpected shock to other input variables or as a response variable of the perturbed system.

Azizpour and Giesecke (2018) showed that contagion is an important factor in understanding bankruptcy cascading and provides as an example the connection between the bankruptcy of Delphi in 2005 and bringing General Motors to the brink of bankruptcy. The contagion spreads because of the exposure between companies. Thus, the contagion and the frailty factor are self-exciting phenomena once they exceed a certain threshold.

Acatrinei (2015) analyzed the contagion of indices in the energy sector with a Markov Switching Garch model and showed the spillover between them when they are in a high volatility regime.

Other authors analyze systemic risk and show that it may be the result of contagion in the financial industry. The work of Goodhart, Sunirand, and Tsomocos (2006) circumscribe a broader basis for defining systemic risk and map contagion as one of the important factors for its description.

Diebold and Yilmaz (2009) seminal paper proposed a measure of interdependence called spillover index, based on the decomposition of variance. The method is attractive because it does not require the definition of "spillover episodes".

Instead, the framework allows the identification of such episodes for different types of assets.

Diebold and Yilmaz (2009, 2012, 2013, 2014, and 2018) have applied the spillover methodology to different types of assets. The methodology can be applied to any network in which common factors are identified such as trade links, capital flows, intra-sectoral links, or changing investor expectations. An extensive econometric literature has developed around this method.

2. Methods

Sims (1980) introduced Vector Autoregressive models (VAR) as a multivariate generalization of univariate autoregressive models. They were initially an alternative to large models of simultaneous equations since Sims argued that empirical research should use smaller models identified with a lesser number of constraints.

A VAR model allows the endogenous treatment of all the variables in the model, and test if a certain variable is exogenous. Because a VAR model can be also written as a VMA (Vector Moving Average) model, the impact of a shock on the evolution of the selected dependent variables can be studied. Variance decomposition indicates the extent to which a particular variable explains the evolution of the variance of another variable and how much of it is attributable to its shock.

A shock in one variable will also affect the other variables, given the dynamic structure of the VAR model. The variance decomposition determines how much of the predicted variance error of a variable is explained by the innovations for each variable. We use the notation of Diebold and Yilmaz (2011) to describe the decomposition of the variance of forecast errors for *H* steps forward:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Sigma A_h A_h' e_i)^2} \quad (1)$$

Where

Σ – variance matrix for the error vector ε

σ_{ij} – standard deviation of the error term for the *j* equation

e_i – selection vector with one as the i^{th} element and zeros otherwise

The sum of the elements in each row of the variance decomposition table is not equal to 1. To use the information available in the variance decomposition matrix, each entry of the variance decomposition matrix is normalized by the row sum as:

$$\widetilde{\theta_{ij}^{g}}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \quad (2)$$

Therefore, the spillover index is computed as:

$$S^{g}(H) = \frac{\sum_{i,j=1}^{N} \widetilde{\theta_{ij}^{g}}(H)}{N} . 100 \quad (3)$$

We have used the European Union's Industrial Production Index (monthly frequency) over the last 10 years (2010-2020). The time series are deseasonalized and stationarized by taking the log-difference. The basic assumption for constructing the spillover index is that the activity of industrial production has a significant role in GDP.

Cluster analysis involves the application of an algorithm to find hidden groups in a data set. Algorithms form clusters so that data in one cluster are more similar than data in another cluster. The measure of similarity on which clusters are created can be defined by different methods: Euclidean distance, probabilistic distance, or another distance. A hierarchical tree is an algorithm that builds a hierarchy on several levels of clusters by creating a cluster tree.

A dendrogram is a type of graphical representation of a hierarchical tree, which consists of many U-shaped lines that connect data points in a hierarchical tree. The height of each U represents the distance between the two connected data points. We have used in our analysis the Spearman distance which is calculated as one minus the Spearman correlation between the observations.

3. Results and discussion

The data used are monthly indices of industrial production in the period 2010-2020 for the following 24 economies: Netherlands, Luxembourg, Croatia, Portugal, Cyprus, Greece, Italy, Sweden, France, Ireland, Germany, Belgium, Slovenia, Latvia, Lithuania, Bulgaria, Austria, Poland, Estonia, Hungary, Czech Republic, Slovakia, Romania, and Spain.

The graphical representation of the dynamics of the Industrial Production Index (Figure no. 1) for the first eight months of 2020 suggests a strong correlation between the economies of the European Union, with a sharp decline in March-April, a brief easing in May-July, and a worsening of the economic situation since August.

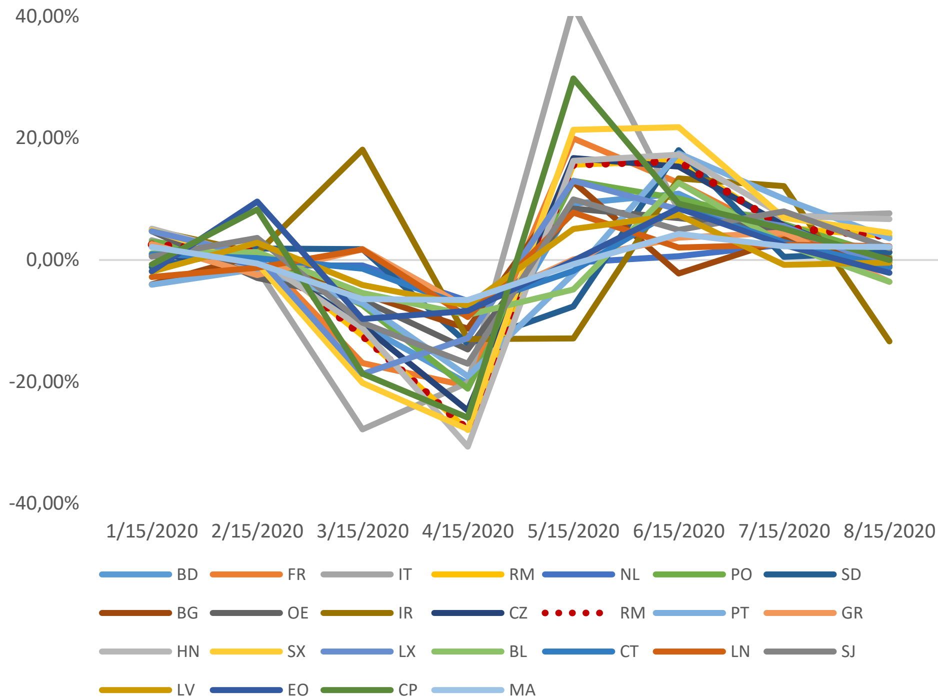


Figure no. 1. Industrial Production Indices (m-o-m %) in the European Union

Source: Refinitiv, author's calculation

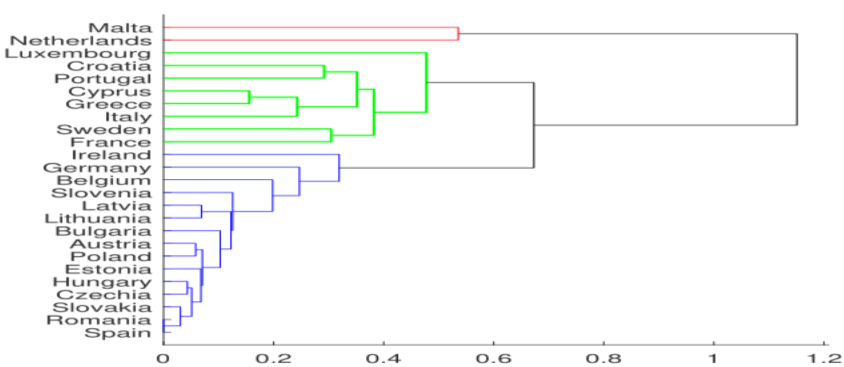


Figure no. 2. Industrial Production Indices' dendrogram

Source: Refinitiv, author's calculation

Figure no. 2 presents the dendrogram for Industrial Production Indices. The dendrogram was made based on the distances between the indices of industrial production, calculated based on the Spearman distance. The resulting data were transformed into a hierarchical cluster type tree, the differentiation is made according to the distance from the median.

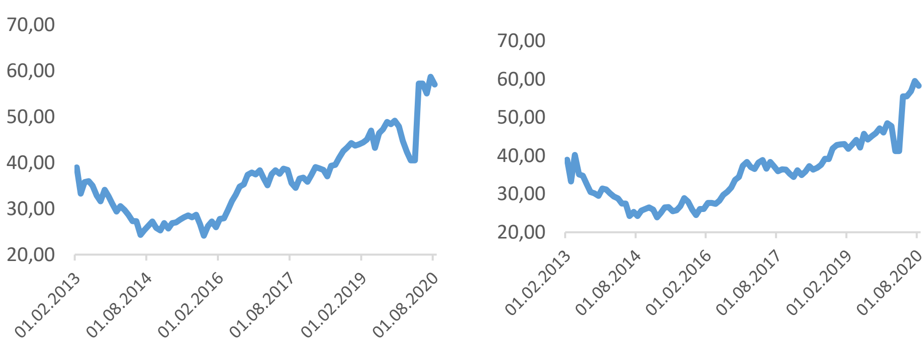
The results indicate that there are two blocs of countries. Malta and the Netherlands have an atypical evolution. The first block of countries contains the following economies: Luxembourg, Croatia, Portugal, Cyprus, Greece, Italy, Sweden, France, and Ireland. The second block of countries contains the following economies: Germany, Belgium, Slovenia, Latvia, Lithuania, Bulgaria, Austria, Poland, Estonia, Hungary, the Czech Republic, Slovakia, Romania, and Spain. The first block is represented in the dendrogram in green and the second in blue.

Using Principal Components Analysis (PCA), we have calculated the principal components for the two country blocks. In the first step, the covariance matrix of the Industrial Production Indices was calculated, and then the PCA method was applied to the correlation matrix. The first Principal Component explains 56% of the variability of industrial production indices for the first bloc of countries and 76% for the second bloc of countries. The first Principal Component is usually seen as the trend. Thus, the results of the PCA method indicate close economic linkages for all economies in the European Union for the last ten years (2010-2020).

In the next step, a spillover index was calculated for each group of countries, and robustness analysis of the estimates was performed. The robustness analysis took into account the length of the mobile window (denoted with *w*) and the forecast horizon (denoted with *h*).

In the first step, the length of the mobile window was increased and the forecast horizon was kept constant. In the second step, the forecast horizon was kept constant and the length of the mobile window was increased.

The first bloc of countries consists of Luxembourg, Croatia, Portugal, Cyprus, Greece, Italy, Sweden, France, and Ireland. Figure no.3 presents the spillover index for the first group of countries.



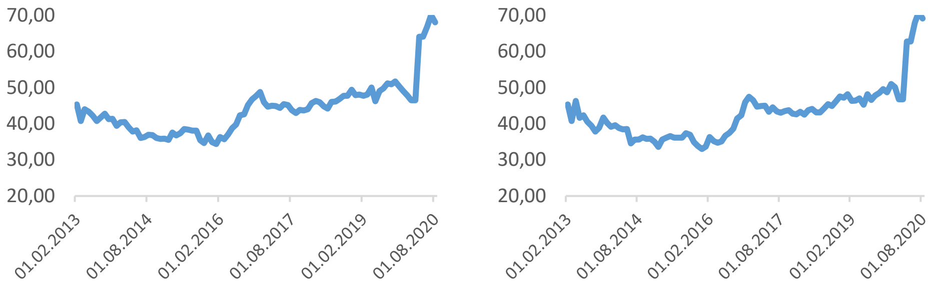
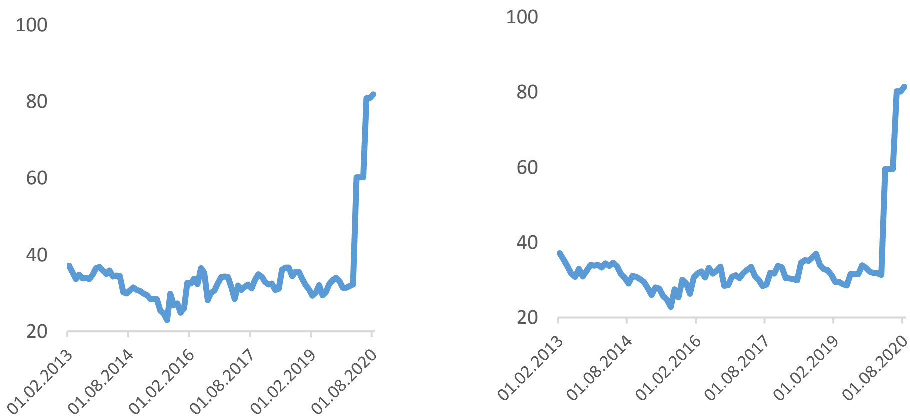


Figure no. 3. Spillover index for the first group of countries
a) H=1, w=36; H=1, w=38
b) H=2, w=36; H=2, w=38
Source: Refinitiv, author's calculation

The second bloc of countries consists of Germany, Belgium, Slovenia, Latvia, Lithuania, Bulgaria, Austria, Poland, Estonia, Hungary, the Czech Republic, Slovakia, Romania, and Spain. The results show that in the first two quarters of 2020, the spillover in the Industrial Production increased similarly for both blocs of countries. The contagion was faster in the second bloc. The accelerated increase in the spillover index was due to the isolation and distancing measures introduced by all European economies. The smaller economies, grouped in the second bloc of countries, had a faster and sharper decline in their Industrial Production Indices, a general response that is reflected in the sharp rise in the spillover index. It remains to be investigated in the future how much contagion each economy receives from Germany, but also the proportion of spillover that the countries in the first bloc of countries transmit. Figure no.4 represents the spillover index for the second block of countries.



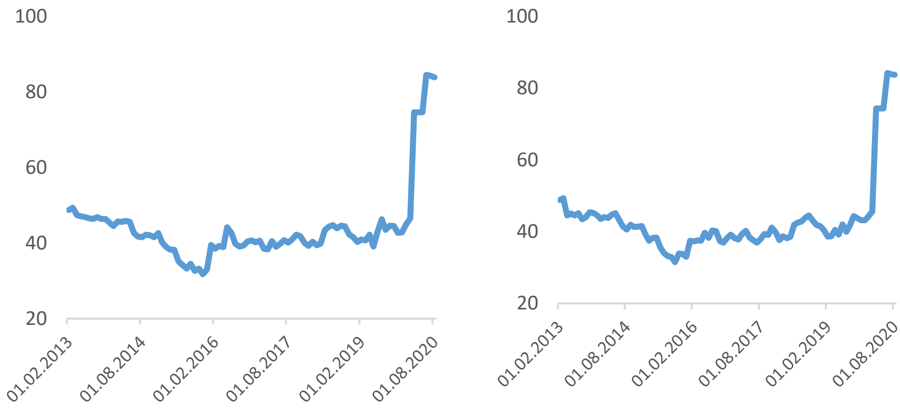


Figure no. 4. Spillover index for the second group of countries
a) H=1, w=36; H=1, w=38
b) H=2, w=36; H=2, w=38
Source: Refinitiv, author's calculation

Conclusions

The methodology of Diebold and Yilmaz (2009) was applied to build a macroeconomic spillover index and some contributions were made to the understanding of the European business cycle.

The application of the methodology proposed by Diebold and Yilmaz (2009) for business cycle analysis is relatively new and rarely used, in practice being preferred the method of extracting the cycle from GDP. From this point of view, the method proposed by Diebold and Yilmaz is superior to the analysis which uses pairs of correlations between economies. The spillover index is based on an Autoregressive Vector model and can detect idiosyncratic fluctuations in several economies.

While some economic debates are centered on how sharp will be the economic contraction generated by the pandemics Covid-19, be it in the shape of U, V, or W, our results show that the recovery will be difficult, as it is determined primarily by the economic stability of the economic group closest to the analyzed country but also that is determined topologically by the economic dynamics of the other economies.

The spillover index for the business cycle is critical for understanding the influences transmitted within the European Union economies. The sudden increase in the contagion index is the strongest in the last ten years, both in terms of speed and network size, and indicates a sudden synchronization of business cycles for the 24 economies studied.

A sudden increase in the spillover index suggests a period of recession or macroeconomic instability and it is comparable in dynamics only to the contagion during the Global Financial Crisis of 2007-2009.

Regarding the different response of the two blocs to the economic shock generated by the pandemics, the results obtained indicate that the smaller, less developed European economies, which are included in the second bloc, absorbed the shocks asymmetrically, amid structural economic problems, which were pre-existing in these economies and experienced a faster decline in economic activity.

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