



## The use of transfer entropy to analyse the comovements of European Union stock markets: a dynamical analysis in times of crises

O uso da entropía de transferencia para analizar os comovements dos mercados bolsistas da Unión Europea: unha análise dinámica en tempos de crise

Paulo Ferreira<sup>1,a</sup> , Dora Almeida<sup>2,b</sup> , Andreia Dionísio<sup>2,c</sup> ,  
Derick Quintino<sup>3,d</sup> , Faheem Aslam<sup>4,e</sup> 

<sup>1</sup> Instituto Politécnico de Portalegre, Portugal

<sup>2</sup> Universidade de Évora, Portugal

<sup>3</sup> University of São Paulo, Brasil

<sup>4</sup> University of Islamabad, Pakistán

✉ <sup>a</sup>[pferreira@ippportalegre.pt](mailto:pferreira@ippportalegre.pt)

✉ <sup>b</sup>[dmfa1982@gmail.com](mailto:dmfa1982@gmail.com)

✉ <sup>c</sup>[andrea@uevora.pt](mailto:andrea@uevora.pt)

✉ <sup>d</sup>[derickdq@alumni.usp.br](mailto:derickdq@alumni.usp.br)

✉ <sup>e</sup>[faheem.aslam@comsats.edu.pk](mailto:faheem.aslam@comsats.edu.pk)

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### Abstract

Understanding the linkages among stock markets holds great importance for investors, policymakers and portfolio managers. When considering the integration of international stock markets and given they are complex systems, it is important to understand how they are related and how they influence each other. Studying data from 25 European Union stock market indices, this piece of research aims to evaluate the dynamics of influence among them. In terms of method, a non-linear approach has been applied, based on transfer entropy with static and dynamic analysis. As the main finding, a strongly influential relationship between some indices should be highlighted. The static analysis allows us to infer that central and western European Union countries are the main influencers, while the dynamic analysis leads us to the conclusion that the relationships between the stock markets have changed over time, revealing their dynamism. The results obtained have several implications. For instance, for investors and portfolio managers, the information about comovements is relevant for diversification purposes and for their decisions on where to make their investments, build portfolio strategies and manage risks; however, for policymakers, the constant monitoring of stock markets may detect increases in the connection between markets, which could be understood as signs of instability.

**Keywords:** bidirectional influence; European stock markets; net transfer entropy; stock market integration; transfer entropy.



## Resumo

Comprender os vínculos entre os mercados de valores reviste gran importancia para os investidores, os responsables políticos e os xestores de carteiras. Ao considerar a integración dos mercados bolsistas internacionais e dado que son sistemas complexos, é importante entender como se relacionan e como se inflúen mutuamente. Estudando datos de 25 índices bolsistas da Unión Europea, esta investigación pretende avaliar a dinámica de influencia entre eles. En canto ao método, aplicouse un enfoque non lineal, baseado na entropía de transferencia con análise estática e dinámica. Como principal achado, cabe destacar unha relación de forte influencia entre algúns índices. A análise estática permite inferir que os países do centro e oeste da Unión Europea son os principais influentes, mentres que a análise dinámica lévanos á conclusión de que as relacións entre os mercados bolsistas cambiaron co tempo, revelando o seu dinamismo. Os resultados obtidos teñen varias implicacións. Por exemplo, para os investidores e xestores de carteiras, a información sobre os comovementos é relevante a efectos de diversificación e para as súas decisións sobre onde realizar os seus investimentos, construír estratexias de carteira e xestionar os riscos; con todo, para os responsables políticos, o seguimento constante dos mercados bolsistas pode detectar aumentos na conexión entre os mercados, que poderían entenderse como signos de inestabilidade.

**Palabras clave:** Influencia bidireccional; Mercados bolsistas europeos; Entropía de transferencia neta; Integración bolsista; Entropía de transferencia.

**JEL Codes:** G01; G11; G15.

## 1. INTRODUCTION

Over recent decades, financial market integration among developed and emerging markets has occurred, with rapid improvements in technology and intense global competition being two of the many contributing factors (Pirgaip et al., 2021). The integration of financial markets can strongly impact financial and economic stability. While, on the one hand, integration among financial markets can help improve an economy's capacity to absorb shocks and foster development, on the other hand, it can also heighten the risk of contagion between markets. Effective portfolio diversification is a key element for international investors and thus research on stock market integration has gained greater relevance.

Since the creation of the euro area, European financial markets have been exposed to five highly relevant but very different events: the introduction of the euro in 2002, the global financial crisis (GFC) of 2008, the 2010 European sovereign debt crisis (ESDC) in most vulnerable economies in the Eurozone (Greece, Ireland, Italy, Portugal and Spain, hereafter GIIPS), the Brexit referendum and most recently the COVID-19 pandemic. Since the introduction of a common currency (the euro), investors have been able to directly access stock markets in the Eurozone, making financial integration more thorough in the monetary union's stock markets (Mylonidis & Kollias, 2010). According to Bekaert et al. (2013), there was also an increase in integration in the European Union (EU) during the economic and financial integration process. However, both the GFC and the ESDC clearly exposed some weaknesses, inefficiencies and asymmetries of the Eurozone, which led to the creation of two distinct groups (core and periphery) for the financial markets and countries involved (Dias & Ramos, 2013), with subsequent financial disintegration in the area (Caruso et al., 2019). Despite this supposed consequence, several studies have suggested that the integration of the financial stock market in the Eurozone continued even with the 2010 ESDC (Büttner & Hayo, 2011; Bentes, 2015; among others). However, there is no consensus on this issue, as is stated, for example, by Gabriel and Pires (2015) and shown in the related literature review. It is also possible to identify several approaches, from Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models (with a vast range of specifications) to event-study approaches or the use of the Diebold and Yilmaz approach, among others (see, for example, Tilfani et al., 2020, or Chakrabarti et al., 2021). Among the most popular are lagged cross-correlation (Ramchand & Susmel, 1998) and Granger causality (Granger et al., 2000), albeit with their limitations; while the former can neither distinguish the possible bidirectional impact between markets nor separate the effects caused solely by the source time series from the environmental effects, the latter can only detect information coming from the source series; besides this, it is also a linear approach, meaning it may not be sensitive to non-linear interactions. Financial markets are complex systems (Korbel et al., 2019), meaning that, like most networks of this nature, they are highly non-Gaussian and non-linear. Thus, these approaches may not be sufficient to explain the dynamics of linkages between markets, indicating that it is important to overcome any limitations identified. Information-based approaches are able to detect information flows and identify their sources appropriately so that they can be used to solve the aforementioned shortcomings. Transfer entropy (TE), introduced by Schreiber (2000) and based on Shannon information entropy, is one such information-based approach, which, in addition to being a tool for measuring both linear and non-linear relationships, is a model-free measure of information transfer between time series. There is no need for any assumption about the underlying probability distribution of the

variables or about the relationship between them (Dionisio et al., 2004) and it is also robust against spurious association (Lizier et al., 2011).

Throughout the history of financial markets, various crises and events have affected them, such as the GFC and the ESDC, the effect of the Brexit referendum and even the recent COVID-19 pandemic, the latter of which is still ongoing. Lastly, stock market behaviour during normal periods and those of turmoil must be not overlooked.

The research questions we would like to address are as follows: (i) Are the European stock markets strongly related or integrated?; (ii) Which are the most influencing stock markets?; (iii) Is this influence static over time, or does it change?; (iv) Is a financial crisis one of the factors that may change the relationship between EU stock markets?

The main objective of this piece of research is to evaluate the dynamics of influence among 25 EU stock markets while considering financial crises, by to studying the complexity of the stock markets and introduce an overall measure for the relationships. More specifically, we hope to evaluate the integration process of the EU stock markets in a general and static way and then compare these results with a dynamic approach. By doing so, we should be able to identify stock markets which could be categorised as “influencers”, give dynamic insights into the bidirectional relationship between markets and identify several crises or events. A sliding windows approach will be coupled to both of the abovementioned approaches.

This study contributes to the existing literature in the following ways: firstly, it explains how the European financial integration process has evolved over time, especially during both recent financial crises (the GFC and the ESDC); secondly, it provides insights into the information flow between European Union stock markets, based on a non-linear and dynamic approach; thirdly, on a similar note to the previous point, it offers a vision that, as it is based on transfer entropy, allows a global and directional evaluation of the complex relationships between markets.

Our main results point to the Central and Western European countries playing the role of influencers, using static analysis. The dynamic analysis allows us to conclude that the relationships between EU stock markets have changed over time, revealing dynamism. Crises and other critical moments in the economies are probably the factors behind the behavioural shift. The remainder of this paper is organised as follows: section 2 maps out a brief literature review; section 3 explains the data and the methods applied; section 4 presents the results (static and dynamic analysis); Section 5 draws our conclusion.

## 2. BRIEF LITERATURE REVIEW

Potential positive and negative effects of stock market integration have been pointed out in several studies, as can be seen, for example, in Bekaert et al. (2013) and most recently in Nardo et al. (2022). However, our main aim in the brief literature review is to understand the dynamics of influence among European stock market indices (both statically and dynamically).

Assessing the behaviour of international stock markets represents a key issue for global investors, portfolio managers and policymakers in dealing with crises spreading from one stock market to another. Globalisation and economic integration have allowed the emergence of stock market integration in the last few decades (Boţoc & Anton, 2020). The GFC and the ESDC accentuated and changed the nature of financial markets, which have become very cautious over the last decade (Niţoi & Pochea, 2019). Furthermore, stock market integration is not static but rather evolves over time, making the assessment of stock market integration a constantly relevant and current issue. Although this paper can be included in the great

number of studies assessing stock market integration, it adds to the current literature as it allows the evolution of this phenomenon over time to be evaluated, using a robust approach to the non-linearities and complex behaviour of these markets. At the same time, as the employed measure is asymmetric, it permits the stock markets which are the main influencers among European ones to be identified.

The literature that analyses the linkages between assets and evaluates the impact of crises (with financial and non-financial origins) and other relevant events on EU stock market integration is extensive and contains many broad-ranging approaches. For financial analysis purposes, both linear and non-linear approaches are usually applied (see, for example, [Gabriel \[2012\]](#) for an application of several non-linear methodologies to analyse volatility in the Romanian stock market). There are also static and dynamic analyses, with a great deal of works using time-varying models. In this section, we focus on some of the most recent papers devoted to the study of EU stock market integration and present a brief overview of them.

[Kenourgios and Samitas \(2011\)](#) and [Horvath and Petrovski \(2013\)](#) have applied different multivariate generalised autoregressive conditional heteroscedasticity models (MGARCH). The first authors capture the impact of the 2007–2009 financial crisis on the time-varying correlation dynamics among the developed and the Balkan stock markets, while the second ones attempt to analyse comovements between Western Europe vis-à-vis Central and South-Eastern European stock markets in the period 2006–2011. The former pair show that stock market dependence is heightened, supporting the herding behaviour which occurred during the 2008 stock market crash. The latter have found that the degree of comovements is much higher for Central Europe whereas the correlation of South-Eastern European stock markets with developed markets is near-zero (Croatia being an exception).

[Sehgal et al. \(2017\)](#) have used seven indicators to assess the relationship between periphery and core EU stock indices. Analysing multiple dimensions of time-varying stock market integration, they have found a distinct level of increased correlation between both groups. Their results also suggest that there are contagion effects when moving from normalcy to periods of crisis, which are notably stronger for large-size economies. Focusing on the GIIPS countries, [Mensi et al. \(2018\)](#) have analysed directional connectedness across different markets and discovered that the GFC and the ESDC intensified volatility spillovers, supporting the effects of financial contagion. The approach they have applied has also led them to identify who the net transmitters and receivers are. Thus, the GIIPS (except Spanish and Greek markets) and the global and regional United States (US) markets have been identified as the net transmitters of shocks, while all the other analysed stock markets are net receivers of shocks. [Stoupos and Kiohos \(2022\)](#) have recently used a vector autoregressive (VAR) approach by way of a GARCH model<sup>1</sup> to investigate the degree of stock market integration in the Eurozone after the end of the ESDC. Their results reveal that it is strong between Germany and euro area core member states but disparate for the euro area's periphery. In contrast, there are only indications regarding the euro area in the integration of eastern Mediterranean and Baltic stock markets with the DAX-30 (Deutscher Aktien Index). Most research employs either the VAR or MGARCH models as the standard methodologies to model stock market indices, returns and volatilities. The spillover indices of [Diebold and Yilmaz \(2009\)](#) allow the dynamics to be determined when it comes to the connectedness of many economic and financial variables, the sources of shock spillovers and most absorbent variables. As a consequence, [Škrinjarić \(2020\)](#) has found a gap regarding the application of

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<sup>1</sup> Fractionally cointegrated vector autoregression (FCVAR) and the realized exponential GARCH model (R-EGARCH).

this methodology to the Central and Eastern European (CEE) and Southern and Eastern European (SEE) stock markets. Estimating the spillover indices of [Diebold and Yilmaz \(2009\)](#) among 11 selected CEE and SEE stock markets from 2010 to 2018, the author discovered an absence of shock spillovers for the Slovakian and Bosnian markets. On the other hand, they have found greater connectedness between the Serbian, Slovenian, Croatian and Romanian markets. Applying another dynamic approach, [Nițoi and Pochea \(2019\)](#) have grouped 24 EU stock markets into developed, emerging and frontier markets and analysed the comovements among them. They have applied a dynamic conditional correlation (DCC) approach and seen that the comovements varied significantly over time, allowing them to distinguish different stages (integration, contagion, herding behaviour, and divergence). The dynamic conditional correlation has also revealed differences between countries, especially in emerging and frontier markets. During the GFC and the ESDC, evidence of contagion was found in EU stock markets, which was more obvious during the most severe episodes of crisis. Economic similarities, such as similar behaviour in macroeconomic variables, were pointed out as possible explanations for different paths of comovements. However, during the crises, such explanations had not been so clear. Considering the same 24 EU stock markets, [Nițoi and Pochea \(2020\)](#) have updated their previous study on dependence patterns. They have added an analysis of the effect of investor sentiment on market correlations to the literature. Their results reveal heterogeneity in time-varying dependence across the markets, with a spillover effect being detected from the periphery euro area. Investors' similar sentiments increase comovements, especially in crises.

The effects of the Brexit referendum on worldwide stock markets have been extensively evaluated. For example, [Burdekin et al. \(2018\)](#) have analysed its impact on a broad scope of international stock exchanges by applying an event-study approach. They have found that the majority vote caused turmoil in stock markets with high (albeit foreseeable) intensity in the Eurozone, especially in countries with higher debt levels, such as the GIIPS. [Škrinjarić \(2019\)](#), also applying event-study methodology, has tested the abnormal cumulative return series and volatility series for significant reactions to the Brexit ballot. Regarding the former, [Škrinjarić \(2019\)](#) has found mixed results. Concerning the latter, Britons were significantly affected by the poll. Applying the detrended fluctuation analysis and the variation of its coefficient, [Guedes et al. \(2019\)](#) have analysed the auto-correlations of all European Union (EU) indices and the cross-correlation between the United Kingdom (UK) stock market and other EU markets. According to these authors, in general, the post-referendum climate has not changed efficiency levels significantly, and as its outcome pointed to a decrease in the cross-correlation coefficient, at that moment in time, the UK was more segmented than other EU countries when compared with the past. Thus, the paper concludes that this political event has influenced European market interdependence but not their efficiency. By dynamically analysing stock integration in Central and Eastern European markets, [Tilfani et al. \(2020\)](#) have adopted a sliding windows approach, jointly with the detrended cross-correlation analysis correlation coefficient. Covering the GFC, the ESDC and the Brexit referendum, the author has shown that the stock markets in the Czech Republic, Hungary, Croatia, Poland and Romania are the best integrated. On the other hand, those of Bosnia, Montenegro, Serbia and Slovakia are the least so. While the levels of integration had increased during the financial crises, the contrary happened during the Brexit referendum.

The COVID-19 disease spread worldwide with varying degrees of intensity, having huge impacts on many countries' economies ([Cantuche, 2021](#)). Its rapid transmission and the accompanying containment measures led to a more severe impact on stock markets than in other outbreaks. However, for the sake of this paper, our analysis is centred on the EU stock

markets, so we will focus solely on these. [Tevdovski and Stojkoski \(2021\)](#) have analysed the comovement of extreme returns in eight SEE stock markets (divided into EU members and accession countries) during the period covering both the GFC and the ESDC crises and the COVID-19 health crisis. They have based their analysis on coexceedances<sup>2</sup> and utilised a multinomial logistic regression procedure. They have found evidence favouring the continuation<sup>3</sup> hypothesis, with the factors associated with the coexceedances differing between the member states and the accession countries. The former depend more on signals from major EU economies, while regional signals mainly impact the latter. [Fang et al. \(2021\)](#) have used the return dispersion model proposed by [Chang et al. \(2000\)](#) to examine whether the COVID-19 pandemic affected herding behaviour in the Eastern European stock market and proved that all Eastern European stock markets were more likely to act this way. Some analyses have been conducted to study directional volatility spillover in 12 European stock markets, representing all four regions of Europe, throughout the health crisis. [Aslam et al. \(2021\)](#) have applied Diebold and Yilmaz's methodology, revealing that since the start of the COVID-19 pandemic, both directional and total directional spillovers have remained high. The maximum intraday gross directional volatility spillovers have been transmitted to other European stock markets by Sweden and the Netherlands, while Poland and Ireland's stock markets have transmitted the minimum.

The Diebold and Yilmaz methodology allows simple and intuitive measurement of directional linkages among global stock markets. However, it may suffer from the limitation of linear parametric modelling ([Diks & Fang, 2017](#)), leading us to apply the TE approach to overcome the identified restrictions and look again at spillovers in the European equity market as a whole by using the non-parametric method. Furthermore, as can be seen from the above literature review, there is a scarcity of studies that dynamically assess integration in all the EU stock markets ([Tilfani et al. \[2020\]](#) being an exception) which have the ability to identify who the main stock market influencers are and which countries are most affected by them.

### 3. METHODOLOGY AND DATA

Analysing causal interactions in financial markets is a challenge for academics. [Granger \(1969\)](#) and his very popular Granger causality promotes the study of the bidirectional relationship between variables, including in financial markets, in a linear approach. Formally, a given variable  $X$  Granger causes another  $Y$ , with lags  $k$  and  $l$ , if  $F(y_{t-1}^{(k)}, x_{t-1}^{(l)}) \neq F(y_{t-1}^{(k)})$  meaning that the past values of  $X$  may explain the current value of  $Y$ .

Despite the usefulness and great importance of the Granger causality, it only captures the linear relationship between variables, ignoring its possible non-linear behaviour. Complex systems, like financial markets, cannot be studied in a comprehensive and in-depth way with only a linear approach. As a consequence, we believe that entropy-based measures present several potentialities to achieve this objective.

As regards communication theory, [Shannon \(1948\)](#) created a measure of the level of information and uncertainty in a given message:

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<sup>2</sup> Negative or positive coexceedances in stock prices are followed by subsequent movements in the same direction.

<sup>3</sup> Represents the number of joint occurrences of extreme returns in a stock market group.

$$H(X) = \int p_X(x) \log p_X(x) dx \quad (1)$$

where  $p_X(x)$  is the density function of the random variable  $X$ .  
For any two variables,  $X$  and  $Y$ , we have

$$H(X, Y) \leq H(X) + H(Y) \quad (2)$$

where the equality holds if (and only if)  $X$  and  $Y$  are statistically independent, i.e.  $p_{X,Y}(x, y) = p_X(x)p_Y(y)$

The joint entropy is given by

$$H(X, Y) \leq H(X) + H(Y) = H(Y) + H(X | Y) \quad (3)$$

since Equation. (2) holds, so  $H(Y) \geq H(Y | X)$  and  $H(X) \geq H(X | Y)$ , meaning that there is a possible reduction of uncertainty in variable  $Y$  by knowing variable  $X$  (and vice versa).

The mutual information between two random variables comes naturally from Equation. (3) being defined by:

$$I(X, Y) = \int_X \int_Y p_{X,Y}(x, y) \ln \ln \frac{p_{X,Y}(x, y)}{p_X(x)p_Y(y)} dx dy \quad (4)$$

where  $p_{X,Y}(x, y)$  is the joint probability distribution function of  $X$  and  $Y$  and  $p_X(x)$  and  $p_Y(y)$  are, respectively, the marginal probability distribution functions of  $X$  and  $Y$ . Mutual information can also be expressed as:

$$I(X, Y) = H(X) - H(X | Y) = H(Y) - H(Y | X) \quad (5)$$

Despite being a good measure for a general test of independence, mutual information does not satisfy the triangle inequality, so it is not useful to assess distance. Because it is not an asymmetrical way to evaluate relationships, it limits its application as a causal measure between financial markets (or any other variables).

On the same lines, Schreiber (2000) proposed a measure of the information flow based on Shannon entropy and, more specifically on mutual information, the TE:

$$TE_{YX}(k, l) = \sum_{x, y} p(y_{t+1}, y_t^{(k)}, x_t^{(l)}) \log \log \frac{p(y_t^{(k)}, x_t^{(l)})}{(y_t^{(k)})} \quad (6)$$

Equation. (6) is a directional measure of the dependence between both variables, with its origin in  $X$  (see, for example, Behrendt et al., 2019). In spite of the similarities between the Granger causality and TE, with both being coincident with Gaussian variables (Barnett et al., 2009), TE is a model-free methodology and does not depend on assumptions like linearity. Furthermore, it is an asymmetric measure and has the ability to capture non-linear effects. Consequently, considering Diks and Fang (2017), this study can thus be viewed as a non-parametric extension of the spillover approach considered by Diebold and Yilmaz (2009), contributing significantly to the related literature. That said, taking into account that there is a need to estimate joint and conditional probabilities, it has been based on a partition method which discretises the data. This is performed by considering the relevance of tails in the distributions (see, for example, Jizba et al., 2012). Information flow may be tested using the



bootstrap method proposed by [Dimpfl and Peter \(2013\)](#), which uses 300 replications to obtain the estimated distribution.

In addition to using TE, we have calculated the net TE, given by  $NET\ TE_{YX} = TE_{YX} - TE_{XY}$ , in order to identify which of the variables in each pair is a net influencer or is net influenced by the other.

TE has been widely used in several research fields (neuroscience, climatology, etc.), including economics and finance. In the latter, we can highlight some papers where this approach has been applied to evaluate the information flow between stock indices, exchange rates, stock markets and cryptocurrencies or between cryptocurrencies and commodities ([Kwon & Yang, 2008](#); [Dimpfl & Peter, 2013](#); [Sensoy et al., 2014](#); [Kim et al., 2020](#); [Huynh et al., 2020](#); [Yi et al., 2021](#); [Ferreira et al., 2021](#); [Assaf et al., 2022](#), among others). Modelling information flows through transfer entropy has advantages, due to the possibility of evaluating such relationships as a whole. In some studies, this analysis is complemented with volatility modelling and with the assessment of volatility transfer between markets (see, for example, [Daugherty & Jithendranathan \(2015\)](#) and [Kuang \(2021\)](#)). In the present study, we will evaluate the transmission of information via returns and therefore models from the GARCH family are not presented.

We have employed a sliding windows approach based on windows of 1000 observations (i.e., close to four years) to evaluate the dynamics of the relationship between indices, which allows a time-varying analysis of the behaviour between variables. In the context of crises and rare events, it is possible to identify how they affect the bidirectional relationship between indices. All the estimations of the TE have been made using the R package RTransferEntropy.

In this paper, we use a set of European Union stock markets. The main goal is to study the relationships among the EU stock markets and compare them against each other. The countries and indices under analysis can be found in [Table 1](#). The dataset consists of daily observations for 25 stock markets in the EU (excluding Luxembourg and Cyprus due to limited data availability). All data has been obtained from the Eikon database, from 3 April 2006 (with the purpose of matching the start of the analysis) to 29 January 2021, with a total of 3870 observations. Subsequently, index prices have been transformed into log-returns as usual, i.e.,  $r_t = \ln P_t - \ln P_{t-1}$ , with  $r_t$  as the return rate and  $P_t$  as the index price in moment  $t$ .

The time evolution of the index series is presented in [Figure 1](#) and the respective returns in [Figure 2](#). As can be seen, there is a similar pattern (in visual terms) in the behaviour of the stock markets, the sovereign crisis being a critical point in our sample.

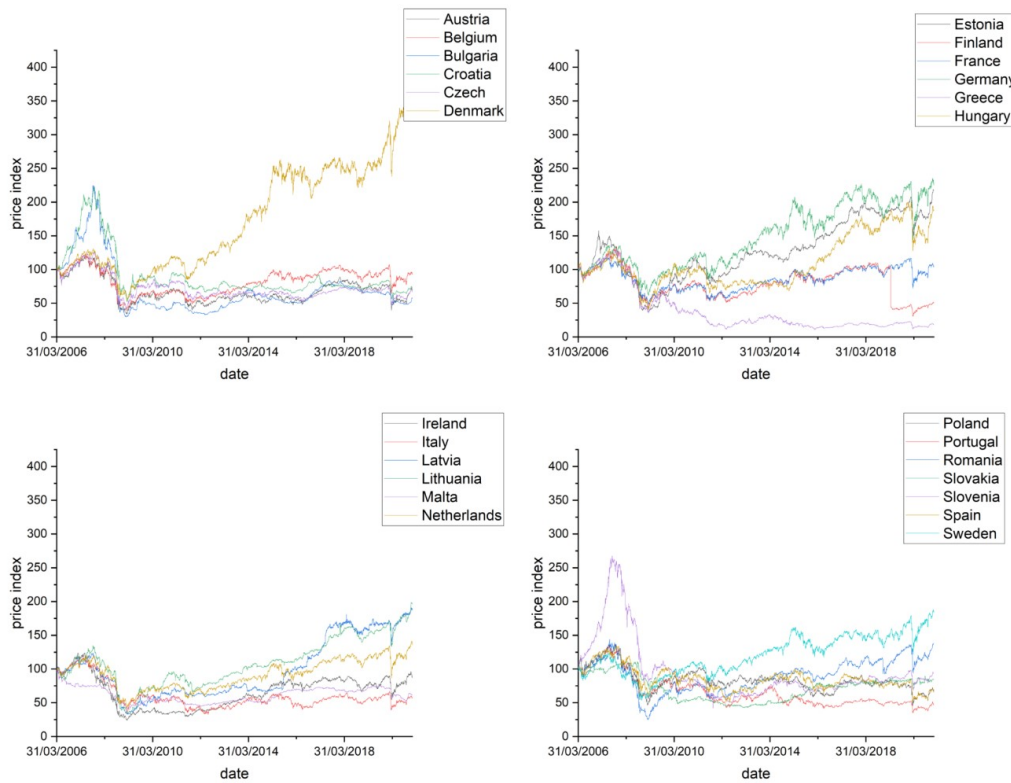
**Table 1. List of countries and indices under study**

Country	Index	Country	Index
Austria	ATX	Ireland	ISEQ
Belgium	BEL20	Italy	FTSE MIB
Bulgaria	SE SOFIX	Latvia	OMX Riga
Croatia	CROBEX	Lithuania	OMX Vilnius
Czech Republic	SEPX	Malta	SE MSE
Denmark	OMX Copenhagen	Netherlands	AEX
Estonia	OMX Tallinn	Poland	WGI 20
Finland	OMX Helsinki	Portugal	PSI 20
France	CAC 40	Romania	BET

Country	Index	Country	Index
Germany	DAX 30	Slovakia	SAX 16
Greece	ATHEX	Slovenia	SBI TOP
Hungary	BUX	Spain	IBEX 35
		Sweden	OMXS30

Note: In this table, we represent the whole set of countries analysed in this study as well as the respective stock market index used.

Figure 1. Time evolution of the 25 EU stock market indices.



**Figure 2. Time evolution of the 25 EU stock market returns**

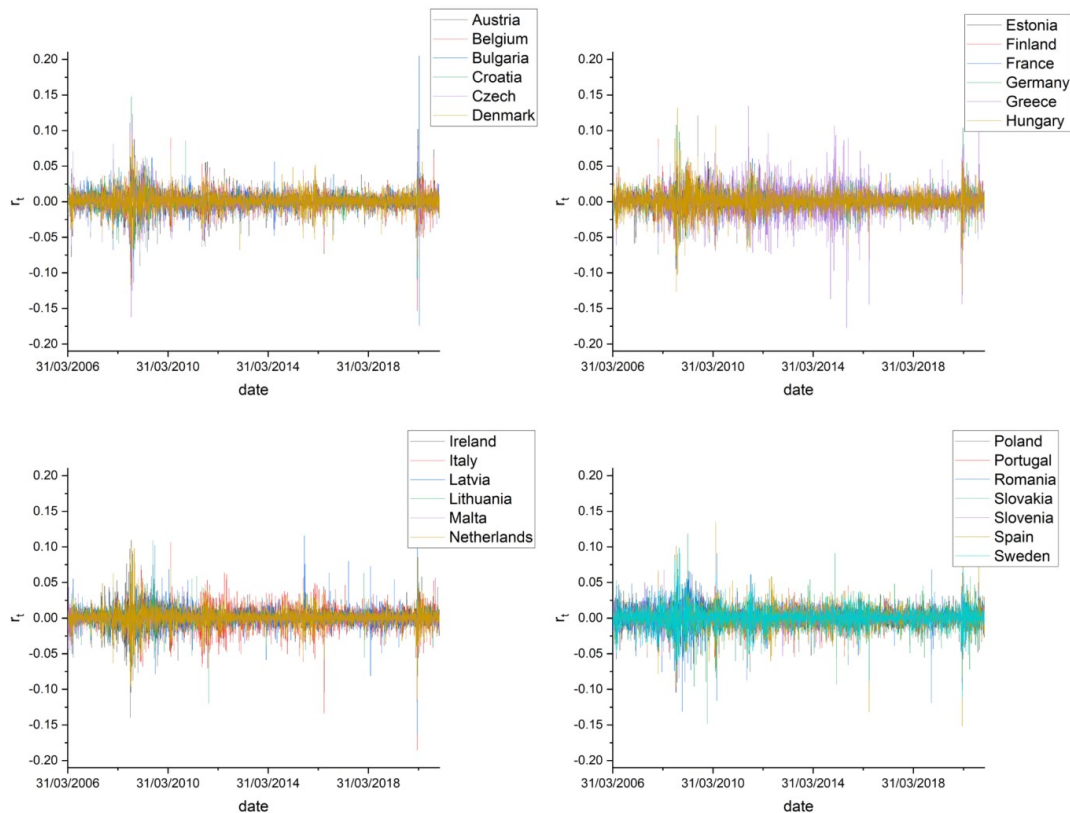


Table 2 shows the descriptive statistics of the daily returns for the stock markets examined. There, it can be seen that, as usual, mean values are near to zero for the whole set of indices, although some of them show a positive mean (i.e., indices which increased in value during the analysis of the sample) while others have a negative mean. The Danish market exhibits the highest average return, followed by Germany's, while the lowest returns are observed in the Greek and Portuguese ones. By using the standard deviation as a measure, the Greek and Italian markets show the most volatility, while the Maltese and Lithuanian ones are the least volatile. With the exception of Latvia, all the countries show indices with negative skewness, meaning that the probability of negative values occurring is higher than for positive ones. Moreover, all the indices show kurtosis levels higher than those consistent with normal distributions, in line with leptokurtic distributions, a very well-known result in financial literature. The stationarity of the returns has also been tested using the augmented-Dickey Fuller test (ADF), in which the null hypothesis of unit root presence was rejected for all the series of returns. All the series reviewed are stationary, allowing analysis with the TE approach.

**Table 2. Descriptive statistics for the indices analysed**

Country	mean	minimum	maximum	std. dev.	skewness	kurtosis
Austria	-9.31E-05	-0.14675	0.12021	0.015861	-0.4923	8.52017
Belgium	-1.98E-05	-0.15328	0.092213	0.012921	-0.66695	10.74985
Bulgaria	-0.000143	-0.17374	0.204952	0.011866	-0.54411	46.12181
Croatia	-7.98E-05	-0.10764	0.14779	0.011003	-0.50332	24.55823

Country	mean	minimum	maximum	std. dev.	skewness	kurtosis
Czech Rep.	-0.000104	-0.16185	0.123641	0.013466	-0.62159	17.56217
Denmark	0.0003305	-0.11723	0.094964	0.012767	-0.32233	6.450758
Estonia	0.0002001	-0.10603	0.120945	0.010323	-0.42664	15.94809
Finland	4.657E-05	-0.10679	0.0885	0.01352	-0.024876	5.36596
France	8.68E-06	-0.13098	0.105946	0.014143	-0.26781	8.258158
Germany	0.0002095	-0.13055	0.107975	0.013816	-0.2288	8.373824
Greece	-0.000441	-0.17713	0.134311	0.019991	-0.47312	7.251433
Hungary	0.000164	-0.12649	0.131777	0.014927	-0.28857	8.924496
Ireland	-3.49E-05	-0.13964	0.097331	0.014827	-0.69204	8.313738
Italy	-0.000146	-0.18541	0.108769	0.01609	-0.66874	9.846588
Latvia	0.0001644	-0.16335	0.120866	0.012336	0.10341	19.69279
Lithuania	0.0001744	-0.11938	0.110015	0.009867	-0.77157	28.0933
Malta	-0.000124	-0.04737	0.057021	0.006347	-0.0145	9.125578
Netherlands	7.933E-05	-0.11376	0.100283	0.01312	-0.36767	9.724172
Poland	-9.97E-05	-0.14246	0.081548	0.014482	-0.49245	5.74959
Portugal	-0.000197	-0.10379	0.101959	0.012639	-0.3925	7.482762
Romania	8.216E-05	-0.13117	0.105645	0.014383	-0.85635	12.308
Slovakia	-4.48E-05	-0.1481	0.118803	0.010955	-1.066	22.5647
Slovenia	-1.6E-05	-0.09383	0.08358	0.01052	-0.70577	10.3282
Spain	-0.00011	-0.15151	0.134836	0.015023	-0.36187	9.728573
Sweden	0.0001574	-0.11173	0.09865	0.013744	-0.18479	5.916146

Notes: For each of the countries examined, this table identifies these descriptive statistics from the respective stock market index: the mean; minimum, maximum and standard deviation (which allow dispersion to be analysed); skewness (to evaluate the symmetry or asymmetry of the distributions); and kurtosis (to analyse whether or not there are fat tails).

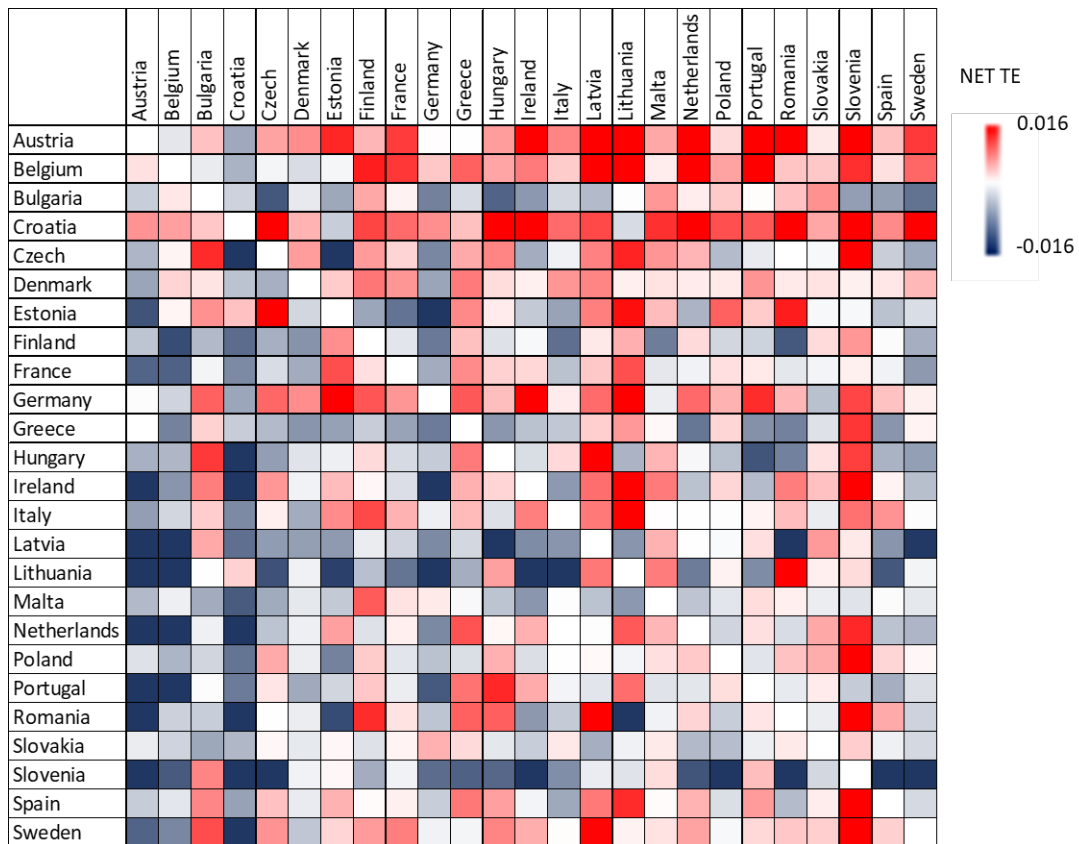
## 4. RESULTS

In this section, we present the results of the TE estimations (bearing in mind the sheer dimension of the table containing the robustness tests, the results are available upon request), splitting them into two different analyses: firstly, a static analysis (analysing the total sample as a whole) and secondly, a dynamic analysis (using the sliding windows approach).

### 4.1. Static analysis

To identify the most affected indices or those which could be considered influencers, considering the whole set of countries tested, we have started by calculating the net TE, defined as  $NET\ TE_{YX} = TE_{YX} - TE_{XY}$ , for all the pairs analysed. The non-linear bidirectional relationship calculated with net TE is presented in the heatmap of [Figure 3](#).

**Figure 3. Heatmap representing the relationship between the indices studied, estimated by net TE (to be read as rows influencing columns). The blue cells mean that the index is net influenced, while the red cells mean that the index is a net influencer. The bolder the cells, the higher the level of influence**

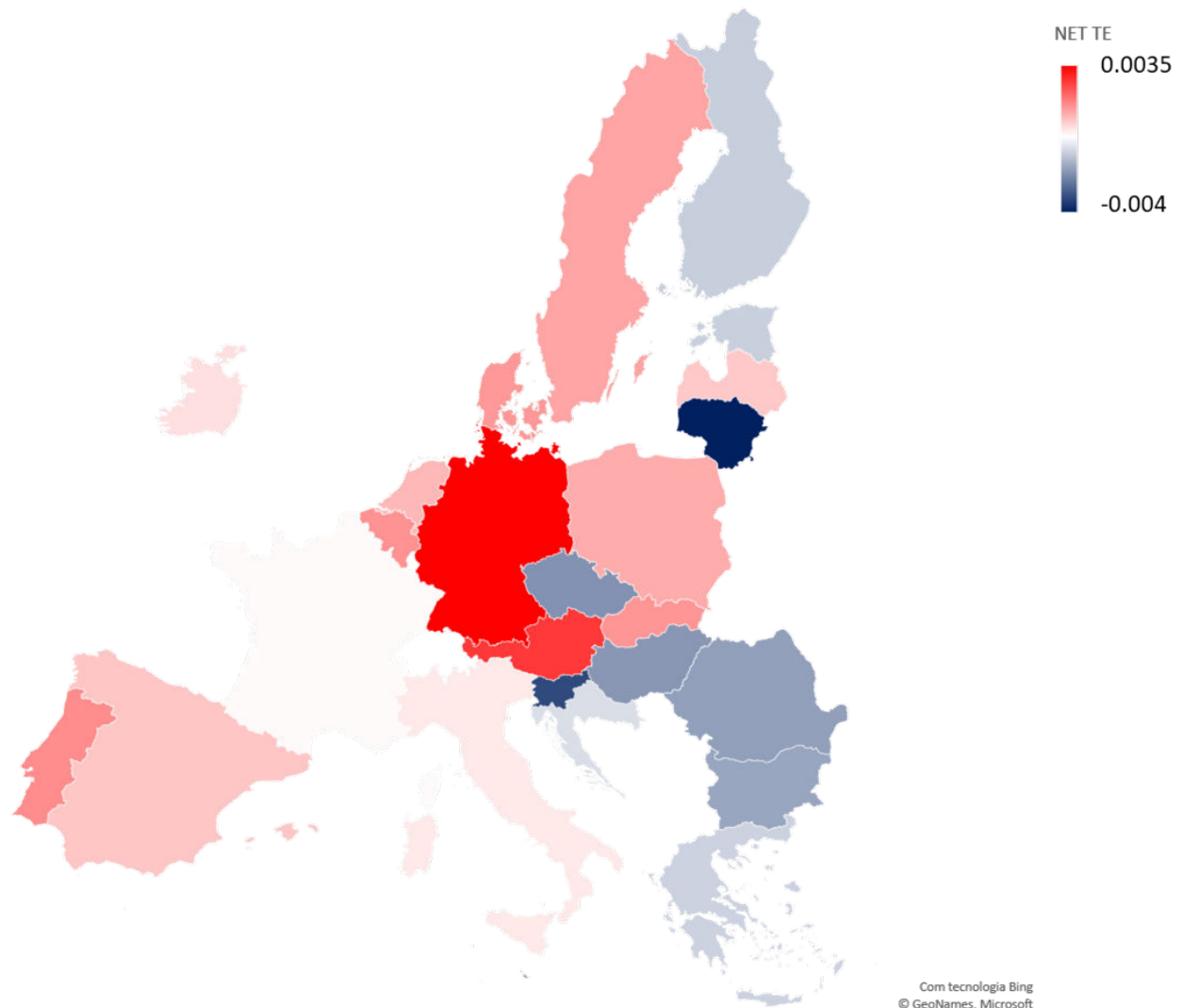


From Figure 3, all 25 European markets analysed share information among one other, this being a sign of integration, corroborating the findings of Iglesias (2015) and Bentes (2015), among others. The results show that among the 25 respective indices, there is a strong, complex and non-linear relationship. The indices of Slovenia, Lithuania, Latvia and Greece are influenced by almost all the others (i.e., more red cells in the respective columns). Conversely, Austria, Belgium, Croatia and Germany are the main influencers (i.e., more red cells in the respective row). Milos et al. (2020) have studied seven Central and Eastern European markets up to August 2018 and found that Slovenian and Croatian ones have the lowest level of dependence out of all of them. In our analysis, the Slovenia is still regarded as having one of the most influenced markets, while the Croatian one is now an influencer. This evidence shows that these two frontier markets have evolved differently over time. We have also noted some indices which share the same TE (e.g., Austria with Germany and Greece), as can be seen from the blank cells (excluding the diagonal ones), meaning they have null net TE. In other words, although these stock markets share information, neither of the stock indices in the pair is a net influencer nor is it influenced.

Considering that the whole set of bidirectional TE values is difficult to read, despite some indices clearly displaying more red values in their rows (for example, Austria, Belgium, Croatia and Germany), we have calculated the mean net TE values for each country and depicted them in a geographical heatmap, which can be seen in Figure 4. In it, we can easily see that Central and Western European countries are more influential in the remaining indices, while Eastern

indices are the most influenced, corroborating evidence found by Horvath and Petrovski (2013) and more recently by Stoupos and Kiohos (2022).

**Figure 4. Geographical heatmap representing the average net TE. Countries in blue represent the respective indices being net influenced, while those in red refer to the respective indices being influencers.**



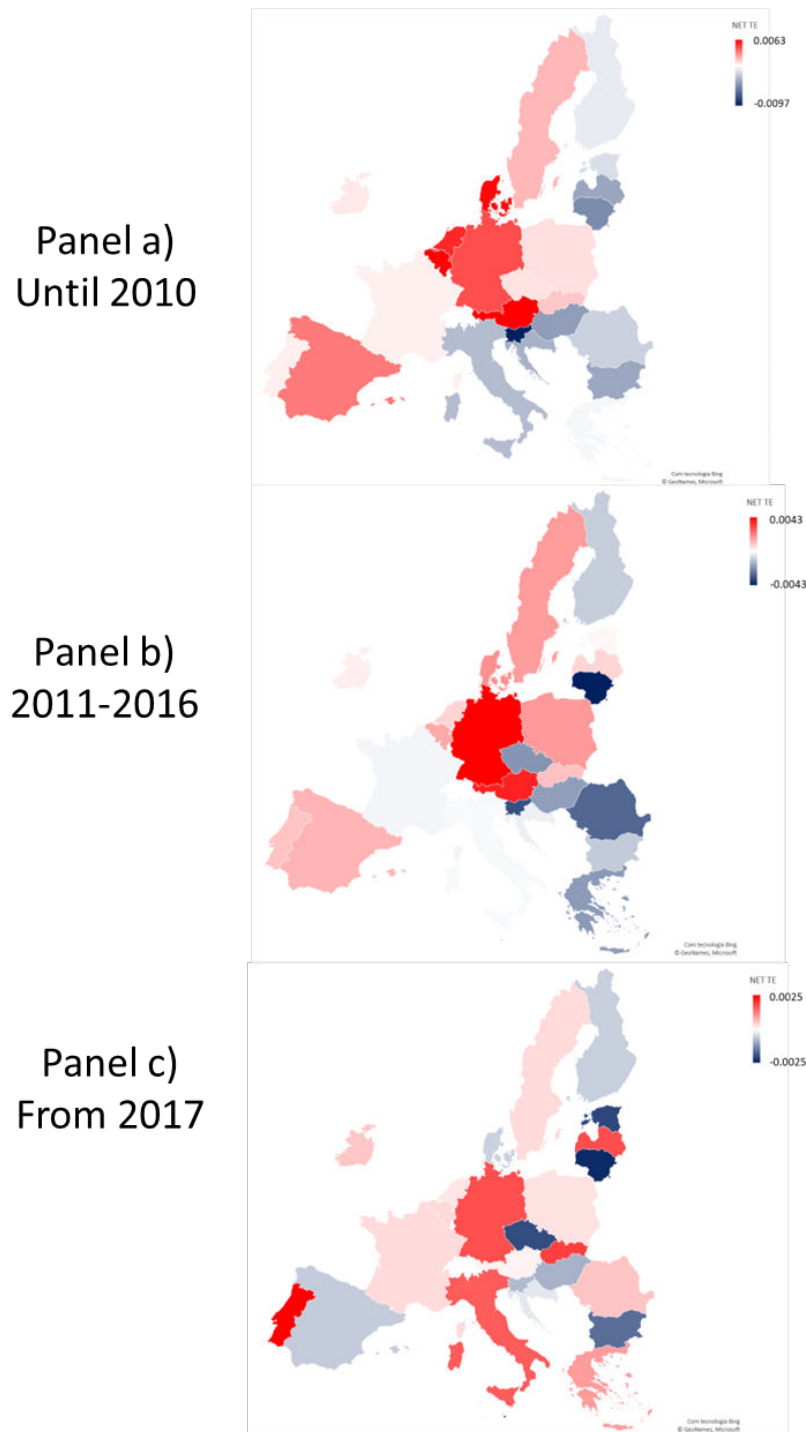
## 4.2. Dynamic analysis

After the first set of analyses, we have proceeded with a dynamic view of the way in which indices influence each other. As previously stated, we have complemented the static analysis of the previous section with the particularity of using a sliding windows approach. With this method, we have calculated the TE sequentially, which has given us the total of the estimations for each pair examined. The time-varying information is important to continuously assess the evolution of the linear and non-linear relationships between indices. With the whole set of TE estimations, we have calculated the average net TE, Figure 5 depicting the mean value for three different periods: until 2010 (Panel a), between 2011 and 2016 (Panel b) and after 2017 (Panel c). The periods have been divided so as to capture the effect of each of them as follows: the global financial crisis appears in panel a; the Eurozone sovereign debt crisis is in panel b; a

calmer period is portrayed in panel c, one which is not affected by financial crises (although there is some effect from the, still ongoing, COVID-19 pandemic).

From the analysis which is represented in Figure 5, we can see some changes in the pattern of bidirectional influence between indices over time. Until 2010, Central European countries (especially Austria, Belgium, the Netherlands, Denmark and Germany) seemed to play an important role in influencing the remaining EU indices, although the Spanish also had some relevant influence on them.

**Figure 5. Geographical heatmap representing the average net TE for three different periods: until 2010 (Panel a), between 2011 and 2016 (Panel b) and after 2017 (Panel c).**



The Slovenian index was subject to the greatest influence. Between 2011 and 2016, the period including the subprime crisis, Germany reinforced its relevance, with several Eastern countries being substantially affected, as shown by the darker blue cells. Some stock indices also changed their conduct: i) the Czech Republic became influenced, while in the previous period it was an influencer; ii) in contrast, Latvia and Estonia became influencers, while in the previous period they were influenced.

Looking at the last panel, indices like the Italian, Portuguese, Latvian and Slovakian ones became more relevant as influencers. Romania and Greece also switched roles, as can be seen from one period to the next. According to [Duttalo et al. \(2021\)](#), the first wave of COVID-19 did not have a significant effect on the volatility of the small European financial centres (such as Cyprus, Estonia, Greece, Latvia, Lithuania, Malta, Portugal, Slovakia and Slovenia) whereas countries with middle to large ones (such as Austria, Belgium, Finland, France, Germany, Ireland, Italy and the Netherlands) were notably affected. This finding could be a possible explanation for the changing role of influencers among the above-mentioned stock markets.

Analysing the three panels simultaneously, indices can be identified that: i) switched from being influencers to being influenced – Denmark, the Czech Republic and Spain; ii) changed from being influenced to being influencers – Latvia, Italy and Greece; and iii) although still being influencers, were less influential – Central European countries.

Our results are in line with other studies, such as [Horvath and Petrovski \(2013\)](#) and [Mensi et al. \(2018\)](#), as regards the evolution of the relationships and the differences between the changes in rules and laws during crisis periods for the countries examined. The role of Central European countries evolved from "strong" influencers to "not very strong" influencers since 2016, indicating that the sovereign crisis and its respective recovery period have changed the way stock markets behave. Changing patterns in the last analysed period could also reflect the different responses of the EU stock markets to the COVID-19 pandemic.

## 5. CONCLUSIONS

The motive for doing this research was to gain a greater understanding of the level of influence among European stock market indices by evaluating them and identifying the relationship between them regarding bidirectional influence. Considering the complexity of the financial markets, we used a non-linear method, namely TE. Our results point clearly to the fact that there are non-linear and complex relationships among the stock market indices analysed as well as integration, which could reduce the opportunities for diversification, a result in line with previous studies (see, for example, [Bekaert et al., 2013](#), [Lee & Nobi, 2018](#)). The static analysis allows us to conclude that the Central and Western European countries studied are the main influencers, as stated in [Skrinjaric \(2020\)](#), among others. However, we have added a dynamic analysis to the existing literature, which helps us comprehend the relationships among EU stock markets, which have changed their behavioural patterns over time, revealing their dynamic sides, in line with the findings of [Nițoi and Pochea \(2019\)](#). Some stock indices went from being influencers to being influenced and vice versa. Several crisis periods (e.g., the subprime crisis, the European debt crisis, the effect of the Brexit referendum and, most recently, the COVID-19 pandemic) are plausible explanations for the changes found in the relationships among the stock indices examined (see, for example, [Wang & Moore \[2008\]](#), [Kenourgios et al. \[2011\]](#), [Guedes et al. \[2019\]](#) and [Tilfani et al. \[2020\]](#)). This evidence alerts policymakers, investors and portfolio managers to the need for close and continuous monitoring of these markets, thus constructing better-prepared portfolios which would be likely to preserve the interests of investors (see, for example, [Skrinjaric \[2020\]](#)).



The broad-ranging results could have different implications and relevance. Concerning investment purposes, current and potential investors might use the information about the linkages to decide where to put their money, how to construct portfolio strategies and what inferences may be made about risk management. The analysis of information flow is pertinent, for example, to identify potential diversification if markets become less connected or, conversely, to make investors aware of the risk of contagion effects if they become more integrated.

Authorities could also use this information in order to try to rebalance possible disequilibrium and instability in financial markets. For instance, a sudden increase in stock market connections when no seemingly relevant events are taking place could be a sign of market overheating, which should be considered a potential contagion risk. Owing to the fact that some phenomena are not easy to foresee, close and constant monitoring of stock markets may detect intensified connections among markets, which could be understood as signs of instability.

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