

6.

CORRELATIONS AND TURBULENCE OF THE EUROPEAN MARKETS

Laurentiu Dumitru ANDREI¹
Petre BREZEANU²
Sorin-Marius DINU³
Tiberiu DIACONESCU⁴
Constantin ANGHELACHE⁵

Abstract

This paper uses stock market data to compute the turbulence index at the European level. We also compute the dynamic matrix of correlations for all pairs of country indices in our sample. Running regressions of the turbulence index on dynamic correlations we attempt to identify the extent to which some particular pairs of correlations may influence the turbulence index more than others, on average. We can therefore infer that portfolios that contain the pairs of indices with the highest explanatory power will have higher exposure to systemic risk when compared with compares that do not contain the respective pairs.

Keywords: turbulence, dynamic correlations, MIDAS regression

JEL Classification: G12, G15

1. Introduction

The interest in the topic of systemic risk associated to financial markets grew significantly since the crisis of 2007. Events such as the bankruptcy of Lehman Brothers or the sovereign debt crisis led to a generalized panic that threatened the normal functioning of the financial system (Silva et al., 2017). Given the recent evolutions that turned the financial sector into one of the landmarks of the global economy, concerns on its potential collapse are fundamental. The numerous negative externalities and huge costs associated to systemic risk that range from bail-outs to drops in GDP growth and unemployment point to the need of its quantitative evaluation.

There is an important number of definitions of the concept of systemic financial risk, but there is consensus on the fact that it describes the probability that the failure of one institution to honor debt obligations may lead to the same failure of other market participants (ECB, 2009). In other words, the malfunction of an institution can be generalized to the entire system,

¹ University of Economic Studies, Bucharest, Romania, E-mail: laurentiu.andrei@gmail.com.

² University of Economic Studies, Bucharest, Romania, E-mail: petre.brezeanu@fin.ase.ro.

³ Institute for Economic Forecasting, Romanian Academy.

⁴ Institute for Economic Forecasting, Romanian Academy.

⁵ University of Economic Studies, Bucharest, Romania.

which leads to chaos in the supply of credit and capital to the economy (Adrian and Brunnermeier, 2016).

Silva et al. (2017) argue that several key factors have been connected to the idea of systemic risk, among which we can find: growth in diversity of financial instruments (Caccioli et al., 2009), financial innovation (Dimsdale, 2009), diversification of individual credit (Battiston et al., 2012), securitization (Battaglia and Gallo, 2013) or leverage (Papanikolaou and Wolff, 2014).

The measurement of systemic risk has been a central point in financial literature, especially during the last period. Xu et al. (2018) argue on the dominance of two measurement approaches. The first one uses confidential information regarding risk positions and exposure obtained from financial institutions. Contributions in this direction can be observed, for example, in Markose et al. (2012). The second approach builds on public data, having as exponents theoretical elements such as: SES - Systemic Expected Shortfall, MES-Marginal Expected Shortfall or the COVAR-conditional Value at Risk.

The evolution of systemic market risk is notoriously monitored by regulatory authorities and market participants. Given the myriad of indicators attempting to capture this risk, one can acknowledge its importance for financial markets in general. The interest in the measurement of this risk is supported by the information that it can provide to market stability and portfolio management in general. Several attempts to develop early warning systems as well as capital requirement measures focus on the interconnections that the financial markets tend to feature. This concentration is motivated by the fact that correlations are changing and they affect portfolio performance in a systematic manner.

We therefore found interest in the analysis of the extent to which correlations are producing systemic risk as well as in identifying which of these connections tend to have a larger impact on this risk. Further analysis could investigate if special events tend to influence these connections more than others, to dissect further on what could be the roots of this phenomenon.

One of the important gauges used for systemic risk is the so-called turbulence index, as computed by Kritzman and Li (2010). Our analysis consists in applying their method on stock market indices from selected European countries to obtain a measure of turbulence. We then compute the correlations for all pairs of countries in our sample using the DCC-GARCH specification, to obtain dynamic correlations. Eventually, we perform several regressions of the turbulence index on the dynamic correlations for each pair and produce these results. This last point in our analysis reflects the extent to which correlations impact the turbulence at the European level and identify those connections with the higher and the lower influence. The paper continues with a section that describes the related literature, a presentation of our data and the methodology we employed, a section of results and it ends with some concluding remarks.

2. Literature Review

Our paper is related to the literature dealing with systemic risk empirical assessment. Moreno and Peña (2013) start from the idea that systemic risk measurement can be conducted on two different paths: macro and micro. The first deals with the analysis of general (macro) indicators with the purpose to determine potential bubbles in the aggregated economy. This approach is endorsed for example by Borio and Lowe (2002) who devise a system of composite indicators capable of capturing potential financial distress. The later perspective considers the micro approach which is based on the financial position of an individual

financial institution. The so-called market-based systemic measures consist of a set of instruments that have been widely discussed in the literature. The MES, proposed by Acharya *et al.* (2012) shows the expected daily drop in equity value when faced by a relevant general shock. Adrian and Brunnermeier (2016) argue in favor of their COVaR that depicts the systemic risk contribution of a certain institution. This is obtained from the difference between the value-at-risk values for perturbation periods versus normal periods. Other relevant measures include the Co-risk (Chan-Lau *et al.*, 2009), the LTD (Weiß *et al.*, 2014) or the SES. Interestingly, Kleinow *et al.* (2017) compare four of these measures (marginal expected shortfall, codependence risk, delta conditional value at risk and owner tail dependence) and conclude that they produce results that differ in a consistent way.

Moreno and Peña (2013) explore six systemic risk measures, namely: principal components for bank CSD, interbank interest rates spreads, structural credit risk models, CDO indices, multivariate densities for CDS spreads and Co-Risks measures and test them for the most relevant banks in Europe and the US. The authors compare these approaches for their samples and determine that the most efficient are the LIBOR-OIS spread for European institutions and principal component CDS for the US market.

In addition to the above-shown measures, the literature developed many other approaches to systemic risk measurement. In a seminal paper, Bisias *et al.* (2012) review 31 measuring techniques for the purpose of capturing systemic risk. Among them we find the financial turbulence model of Kritzman and Li (2010), which will be exploited later in this paper.

A selection of literature focuses on contagion or propagation effects when considering the systemic risk. Dasgupta (2004) demonstrates the way in which the connection among financial institutions can lead to breakdowns. Billio *et al.* (2012) study several econometric approaches for connectedness that are based on Granger-causality networks and principal-components analysis and use them for four financial sectors. The authors notice a growth in relations between the four financial sectors that can be translated into an increase in the systemic risk.

Albu *et al.* (2017) study the potential of systemic risk generation and absorption for several industries. They employ a Cornish-Fisher VaR in order to determine the difference between its output and that of a classical VaR. The paper uses intraday data for 573 of the 600 companies of the STOXX600, which are organized into 24 industries. In a Granger analysis, Albu *et al.* (2017) aim at the spillover effects existing among these industries. They conclude that Automobiles and Components, Software and Services, Transportation are the industries capable to generate the most amount of risk. Corsi *et al.* (2018) use the in-tail Granger-causality test and construct networks between a relevant set of systemically important banks and sovereign bonds.

In a very recent contribution, Lupu *et al.* (2018) study the idea of fragility for a set of six CEE countries. Their methodology is able to determine the contribution brought by each country to the total fragility of the system. Lupu *et al.* (2018) extrapolate the original absorption ratio developed by Kritzman, Li, Page, and Rigobon (2011) for both returns and standard deviations originating from a GARCH (1,1) model. Moreover, an additional robustness analysis is provided by incorporating a European Sentiment indicator. As noted by the authors, the indicator includes provisions for industrial confidence, construction confidence, services confidence and retail trade confidence (Lupu *et al.*, 2018). The paper demonstrates a relevant connection between the sentiment component and the fragility component.

In an investigation related to our paper, Xu *et al.* (2018) employ a CoVAR approach for the Chinese banking sector. They present a modified version of the DCC-MIDAS suitable to study the fat-tailed financial returns.

3. Data and Methodology

Our market data covers daily values of Total Market Indices computed by DataStream for the period between January 2nd, 2012, and January 30th, 2019. The analysis was performed for the following countries: Austria, Italy, Germany, Romania, France, the Netherlands, Portugal, Spain and the United Kingdom, totaling a set of 1848 daily log-returns.

The methodology used for the computation of the turbulence index is a Mahalanobis measure applied to stock market returns, as according to Kritzman and Li (2010). Given a matrix of covariances, Σ , and a vector of averages, μ , for a set of vectors, we can compute the Mahalanobis distance of an individual vector, y , as

$$d = \sqrt{(y - \mu)\Sigma^{-1}(y - \mu)'}.$$

According to Chow *et al.* (1999), this measure is a proper gauge for the “unusualness” of a cross-section of returns when compared with the historical distributional properties of this multivariate dynamics. Given the stylized fact that distributions of log-returns are time-dependent, we can revise the turbulence index as

$$d_t = \sqrt{(y_t - \mu)\Sigma^{-1}(y_t - \mu)'}$$

where we can denote by d_t the turbulence for a certain period t and use the vector y_t to represent the vector of log-returns belonging to the stock indices we took into account for the same period, t . Under this setting, we would consider Σ as the variance-covariance matrix, which is fixed for the set of log-returns, *i.e.* it is the unconditional variance-covariance matrix.

This approach allows us to consider as “turbulent” a certain period t if the measure d_t exceeds a certain threshold, while the rest of the periods we analyze could be considered as “calm”. In their survey on systemic risk measurement, Bisias *et al.* (2012) suggest the use of the 75th percentile for this threshold, which is a view that we also embrace in our analysis. However, the element that is most important for our investigation is actually the index itself. Our objective is to detect the extent to which the dynamics of the correlations impose a change in the values of this index, making markets look more “turbulent”. The identification of such dependences has to rely on a proper measure of the dynamics of correlations, which is performed by employing the DCC-GARCH methodology⁶.

According to this approach, a GARCH (1,1) model is first calibrated on each series of log-returns. This produces daily standard deviations, which further allow for the computation of standardized returns $z_t = \frac{R_t}{\sigma_t}$, where R_t and σ_t are the raw log-return and the standard deviation produced by the GARCH (1,1) model at moment t , respectively. Modeling the covariance of standardized returns is equivalent to an analysis of the correlations of raw returns as:

$$Cov(z_{i,t}, z_{j,t}) = Cov\left(\frac{R_{i,t}}{\sigma_{i,t}}, \frac{R_{j,t}}{\sigma_{j,t}}\right) = \frac{1}{\sigma_{i,t}\sigma_{j,t}} Cov(R_{i,t}, R_{j,t}) = \rho_{ij,t}$$

⁶ The MFE (Matlab for Financial Econometrics) tool developed by Kevin Sheppard was used to develop this part of our analysis.

The standard DCC model employs the transformation of the correlation $\rho_{ij,t}$ by employing an auxiliary variable, usually denoted by $q_{ij,t}$ so that

$$rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$$

The relation of this auxiliary variable with the standardized returns z_t is governed by a specification inspired from the standard GARCH (1,1) model, *i.e.*

$$q_{ij,t+1} = \bar{\rho}_{ij} + \alpha(z_{i,t+1}z_{j,t+1} - \bar{\rho}_{ij}) + \beta(q_{ij,t} - \bar{\rho}_{ij}), \quad \forall i, j$$

where: $\bar{\rho}_{ij}$ is the long term correlation coefficient between log returns i and j .

In a matrix format, we can denote the correlation matrix ρ_t by

$$\rho_t = Q_t^* Q_t Q_t^*$$

where we consider Q_t to be a positive definite matrix that characterizes the dynamics of these returns. We rescale this matrix into Q_t^* to force each element $|q_{ij,t}| < 1$.

$$Q_t^* = \begin{pmatrix} \frac{1}{\sqrt{q_{t,11}}} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \frac{1}{\sqrt{q_{t,KK}}} \end{pmatrix}$$

We then allow Q_t to follow an ARMA process of the type:

$$Q_t = (1 - \zeta - \xi)\bar{Q} + \zeta\epsilon_{t-1}\epsilon'_{t-1} + \xi Q_{t-1}$$

where: \bar{Q} is the $(K \times K)$ matrix of unconditional covariance of ϵ and ζ and ξ are parameters that have to comply with the restriction of positive definiteness (*i.e.* $\zeta, \xi > 0$) and stationarity ($\zeta + \xi < 1$).

For each moment t , the result of our estimation will consist in a series of correlation matrices of the form

$$\begin{pmatrix} 1 & \dots & \rho_{1,K,t} \\ \vdots & \ddots & \vdots \\ \rho_{K,1,t} & \dots & 1 \end{pmatrix}$$

The Mahalanobis distances, *i.e.* our measures of turbulence, rely on daily data to produce turbulence indices at weekly frequency⁷. We use data from each week to compute the variance-covariance matrix for that particular week and return the turbulence index with this frequency. This is why in order to conduct our investigation of connections between daily correlations and turbulence we have to rely on techniques that take into account the different frequencies, *i.e.* weekly for turbulence and daily for correlations. Even though we could compute weekly averages for the correlation dynamics, we decided to employ a

⁷ Kritzman and Li (2010) propose the use of the same measure to compute monthly indices.

methodology that is heavily used in the recent literature to combine different frequencies – the MIDAS regression⁸.

The basic specification for the MIDAS with h steps ahead when we dispose of high frequency data up to point x_t^H is:

$$y_{t+h}^L = a_h + b_h C(L^{1/m}; \theta_h) x_t^H + \varepsilon_{t+h}^L$$

where:

$$C(L^{1/m}; \theta) = \sum_{i=0}^N c(i; \theta) L^{i/m}$$

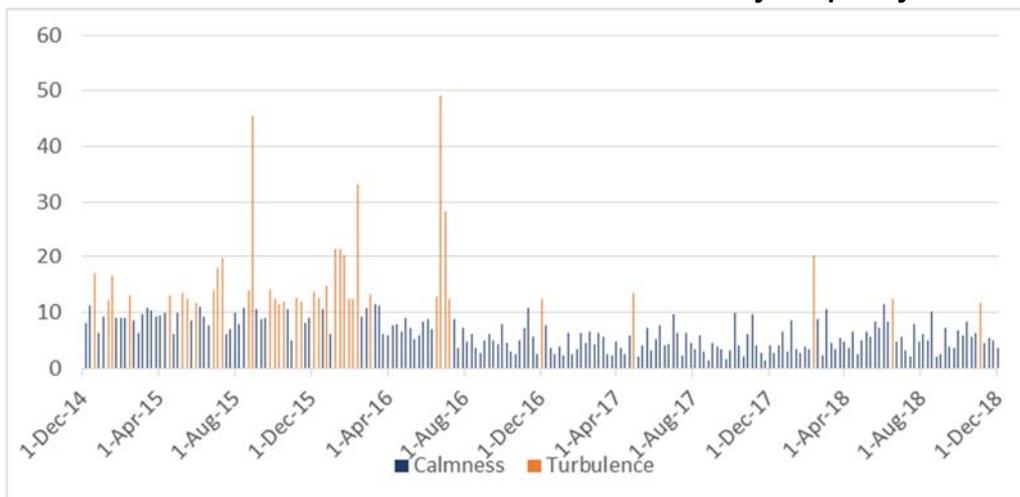
$$C(1; \theta) = \sum_{j=0}^N c(j; \theta) = 1$$

4. Results

As explained in the previous section, we employed the Kritzman and Li (2010) methodology to compute the turbulence index for the whole sample and for all the countries. We developed the analysis to account for daily data, rather than monthly ones, and we compute the Mahalanobis distance for each week in the sample, resulting in 368 measures.

Figure 1

The Evolution of the Turbulence Index and Weekly Frequency



⁸ The Mixed Data Sampling approach was introduced by Andreou, Ghysels, and Kourtellos (2013). For particularities in financial applications see, for example, Albu et al. (2015) or Lupu and Calin (2014). We are using here the Matlab code developed by Ghysels (MIDAS Matlab Toolbox – 2017).

The evolution of this index is shown in Figure 1. We notice that the index captures very well the periods with high turbulence. The highest concentration and largest values were recorded on July 2016, as result of the Brexit vote in the UK. This correlates largely with the high volatility, large market drop and negative sentiment governing the markets during that month. A large value in the third quarter of 2015 is related to the stock market drop as result of China growth deceleration and decrease in the oil prices. We also note that December, the same year, showed significant increase in the index, as result of elections in the US, while February 2018 showed large values as result of the speculation on volatility (the XIV episode in the US).

In general, we may suppose that the evolution of this index is closely related to market events that had the propensity to produce significant changes in total volatility, which is usually correlated with negative log-returns, i.e. series of significant price drops. Our sample consists of the most important stock market in Europe, which makes the evolution of this index even more relevant in terms of financial stability indicator. An interesting remark from this perspective is also that the calmness periods are dominating and they reflect the realm of normality in the financial markets, i.e. those situations when markets evolve in an ordinary, regular manner. For instance, the period governing the last part of 2017 is dominated by low values of the turbulence indicator. This was a period when the hedge funds have generally focused on speculating on the long lasting of the low volatility regime, which gave birth to the famous XIV product, assumed to have generated the short crisis from February 2018⁹.

The previously-mentioned DCC-GARCH methodology rendered the evolution of dynamic conditional correlations for all the pairs in our sample. This yielded 36 vectors accounting for all possible combinations of pairs. Figures 2 and 3 show these dynamics for a set of selected countries. The most important feature that can be extracted from these charts is that the correlations lie mostly at the 0.5 level, on average, and they tend to be larger for some pairs and less important for some other pairs. However, from the time evolution perspective, we notice that their values are less volatile for each pair – the changes are more important from the cross-sectional paradigm and less so from the time series perspectives. The small values belong to the connections of the respective countries with the log-returns belonging to the Romanian stock market index. We notice that it is consistent across all the developed countries used in our sample.

⁹ XIV stands for „Velocity Shares Daily Inverse VIX Short-Term exchange-traded note”, a financial product issued by Credit Suisse that aimed at providing the opposite return to the CBOE Volatility Index VIX. Further details on market dynamics around this volatility episode is documented here: <https://www.cnbc.com/2018/02/05/xiv-exchange-traded-security-linked-to-volatility-plummets-80-percent.html>

Figure 2

Evolution of Correlations (All Pairs of Stock Market Indices)

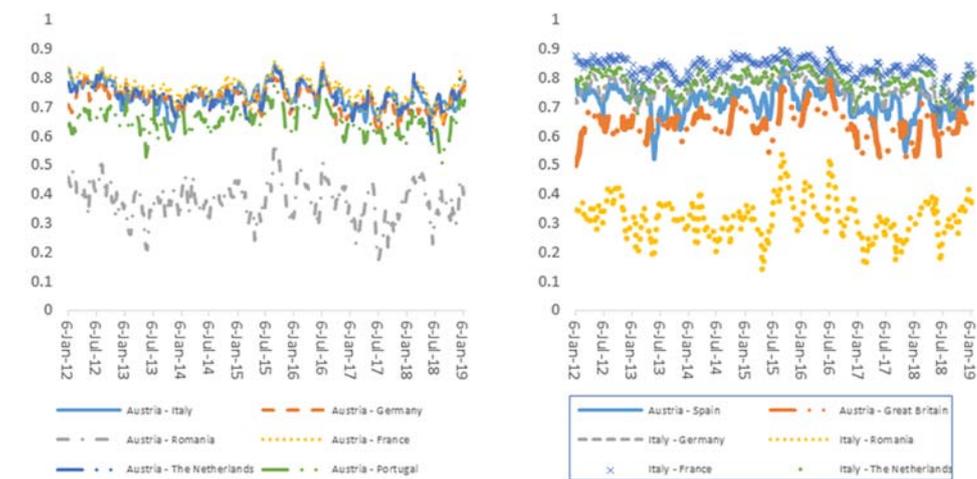
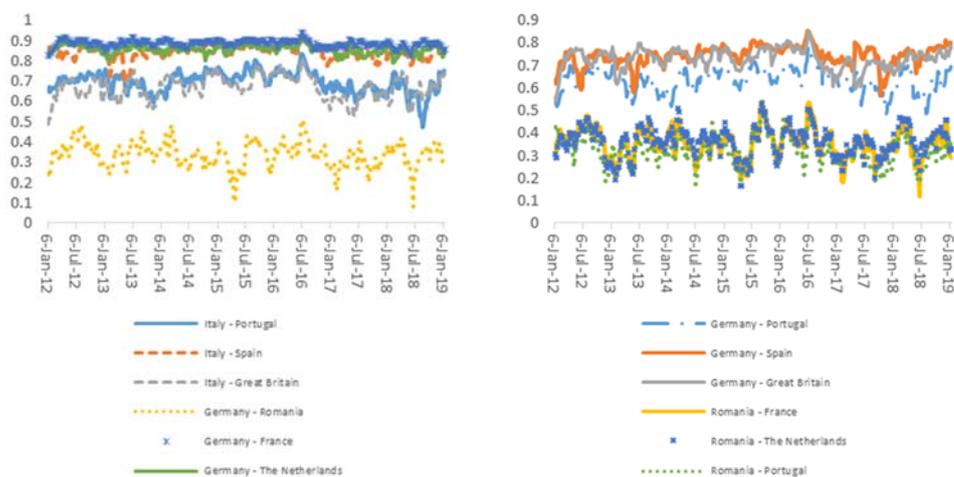
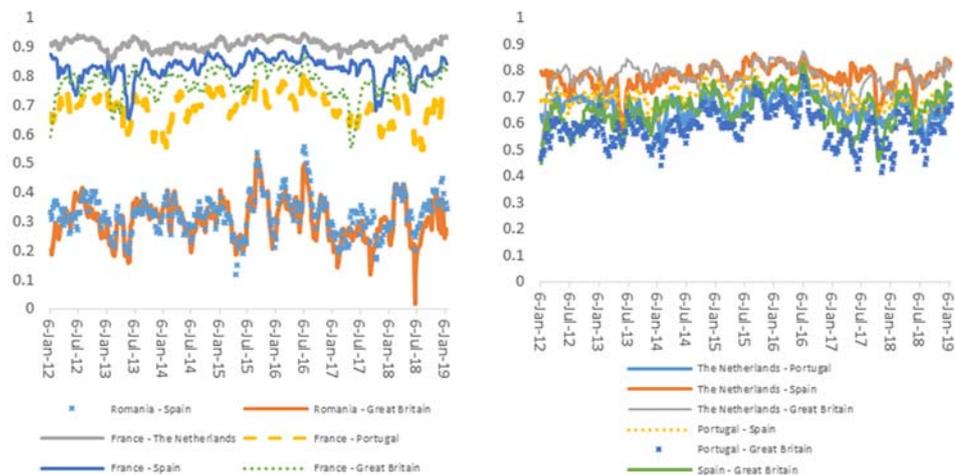


Figure 2 Cont.

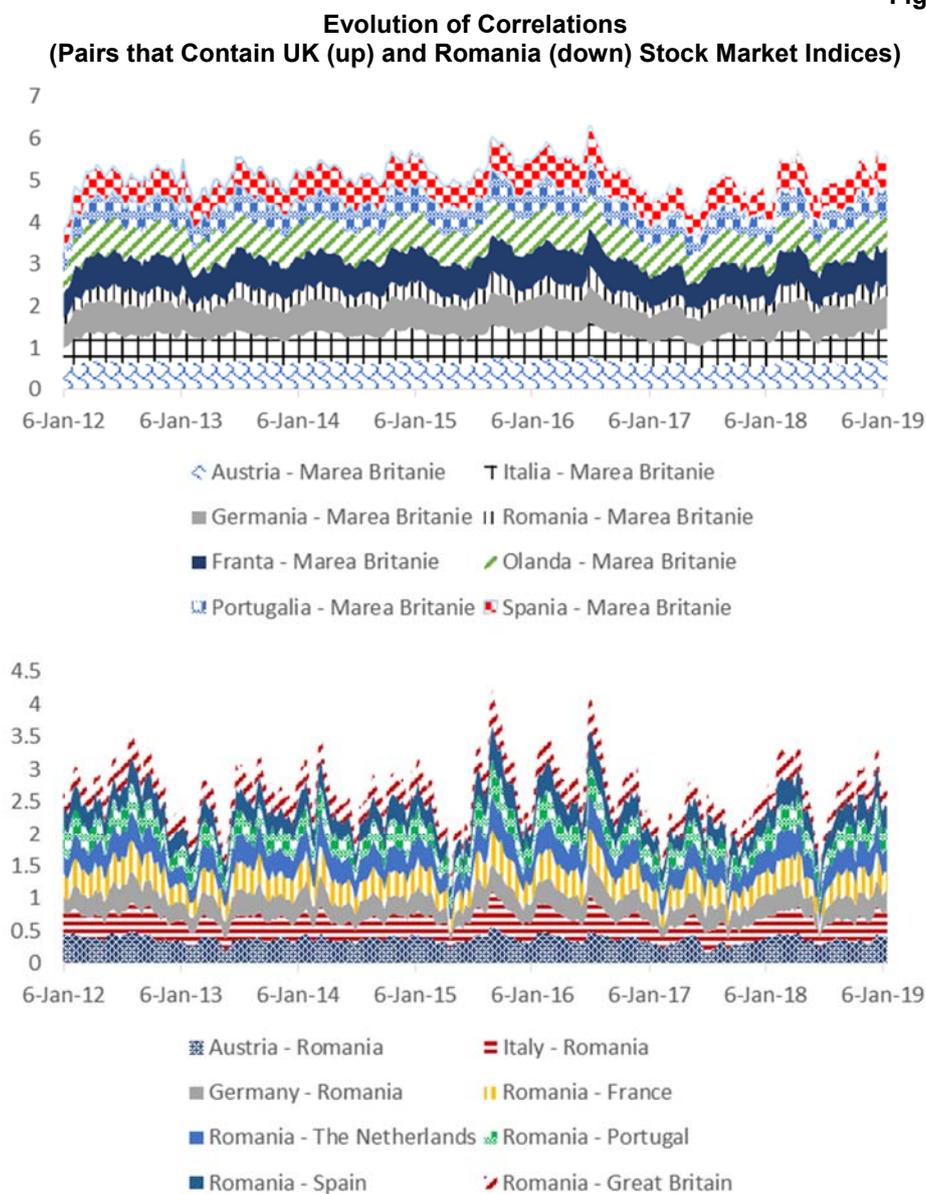




The low values of the correlations with the Romanian stock market, despite their proof of low level of financial integration of our country, have also to be observed in their evolution. The levels tend to be larger towards the end of the sample, which could be seen as proof that our market tends to achieve large levels of integration. However, these low levels are invitations to invest in this financial market, as negative movements in the European markets may also be less important for investments in the local companies listed at the Bucharest Stock Exchange. Transition to the Emerging market status may also reduce this effect in the future.

Figure 3 shows the connections with both the UK and Romania. These correlations are important from the perspective of the Brexit vote in the UK and the frontier status of the Romanian market.

Figure 3



From the UK perspective, we may see that correlations tend to slightly diminish after 2016, reflecting the negative market sentiment about Brexit. A negative jump in these correlations is easily perceived in July 2016, when the Brexit vote took place. The reduction of the influence of the UK to the rest of the European developed countries could be explained by the lower performance of the British index following the Brexit vote event.

From the perspective of the Romanian market, we notice that the values of correlations are the smallest with the stock market indices from the countries in our sample. This phenomenon is consistent with the fact that Romania belongs to the group of frontier markets, while the rest of the countries are developed markets. We notice, however, an important level of volatility for these correlations, with higher values towards the end of the analyzed period. This might be seen as result of the effort of our country to develop and gain the status of emerging market. It is also a possible effect of the attempt to achieve more financial integration with the rest of the developed European countries.

The rest of our analysis consists in presenting the results of several MIDAS regressions performed for the turbulence index as dependent variable and each pair of correlations as explanatory variable. These set of regressions are simple regressions, in which only one pair of correlations is used.

Table 1 shows the values of coefficients of determination for each of these regressions. We decided to keep the mean values for these R2 indicators across a set of MIDAS regressions, as explained in the methodology section.

Table 1

R² Values for Regressions of the Turbulence Index on Each Pair of Correlations

	Austria	Italy	Germany	Romania	France	The Netherlands	Portugal	Spain	Great Britain
Austria		0.0893	0.1502	0.0306	0.1566	0.0969	0.0285	0.0421	0.0031
Italy	0.0893		0.0026	0.0039	0.1233	0.0211	0.0648	0.0031	0.0000
Germany	0.1502	0.0026		0.0183	0.0384	0.0542	0.0087	0.0623	0.0023
Romania	0.0306	0.0039	0.0183		0.0142	0.0004	0.0271	0.0020	0.0074
France	0.1566	0.1233	0.0384	0.0142		0.0000	0.0141	0.0056	0.0044
The Netherlands	0.0969	0.0211	0.0542	0.0004	0.0000		0.0028	0.0609	0.0000
Portugal	0.0285	0.0648	0.0087	0.0271	0.0141	0.0028		0.0013	0.0009
Spain	0.0421	0.0031	0.0623	0.0020	0.0056	0.0609	0.0013		0.0516
Great Britain	0.0031	0.0000	0.0023	0.0074	0.0044	0.0000	0.0009	0.0516	
Averages	0.0747	0.0385	0.0421	0.0130	0.0446	0.0295	0.0185	0.0286	0.0087

A straightforward interpretation of these results is that turbulence on the European capital markets is rather dependent on the connections of the Austrian capital market with the rest of the markets, while the connections with the United Kingdom are less important for the evolution of turbulences. The values of coefficients of determination are not very large because we expect more factors to influence the dynamics of this index. However, we consider that these regressions reveal the extent to which the bilateral linear connections of the stock markets contribute to the generation of systemic risk at the European level.

5. Conclusions

Our paper used daily stock market data for a set of developed countries from the European Union and Romania to investigate the extent to which the correlations among these countries contribute to the overall turbulence of the whole sample of these countries. The importance of systemic risk measurement, both for regulators and market participants, spurred the development of several indicators used as gauges for this phenomenon. They are used as ingredients in the development of early warning systems, the implementation of measurements for capital adequacy purposes or the settlement of hypotheses in the development of stress tests. This paper employs the turbulence index as implemented by

Kritzman and Li (2010) and further refined by Bisias et al. (2012). This indicator is applied on daily data to produce weekly measures of turbulence, which are further related to daily dynamic conditional correlations to investigate their influence on generating market risk. We use the DCC-GARCH methodology to compute the daily correlations and a set of MIDAS regressions to investigate the dependence of the turbulence index, as dependent variable, on each pair of correlations. Our findings show that there are some pairs with a higher influence on turbulence than other pairs, which has important implications on the construction of investment portfolios at the European level. The core of the connections seems to be the Austrian market followed by the connections with the French and the German stock markets. The connections with United Kingdom have less impact on the evolution of the turbulence index for the European financial market as a whole.

References

- Adrian, T. Brunnermeier, M., 2016. CoVaR. *American Economic Review*, 106(7), pp.1705-1741.
- Albu, L.L. Lupu, R. and Călin, A.C., 2015. A Comparison of Asymmetric Volatilities across European Stock Markets and Their Impact on Sentiment Indices, *Economic Computation and Economic Cybernetics Studies and Research*, 49(3), pp. 5-20.
- Albu L.L. Lupu, R. and Călin, A.C., 2017. Risk Generating Industries for European Stock Markets. *Economic Computation and Economic Cybernetics Studies and Research*, 51(4), pp. 5-17.
- Andreou, E. Ghysels, E. and Kourtellos, A., 2013. Should Macroeconomic Forecasters Use Daily Financial Data and How?. *Journal of Business & Economic Statistics*, 31 (2), pp. 240–251.
- Battaglia, F. and Gallo, A., 2013. Securitization and systemic risk: An empirical investigation on Italian banks over the financial crisis. *International Review of Financial Analysis*. 30, pp.274–286.
- Battiston, S. et al., 2012. Default cascades: when does risk diversification increase stability? *Journal of Financial Stability*, 8, pp.138-149.
- Billio, M. Getmansky, M. Lo, A.W. and Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104, pp. 535–559.
- Bisias, D. Flood, M. Lo, A.W. and Valavanis, S., 2012. A survey of systemic risk analytics. *Annual Review of Financial Economics*, 4(1), pp.255-296.
- Borio, C. and Lowe, P., 2002. Assessing the Risk of Banking Crisis. *BIS Quarterly Review*, December, pp. 43-54.
- Caccioli, F. Marsili, M. and Vivo, P., 2009. Eroding market stability by proliferation of financial instruments. *The European Physical Journal B*, 71(4), pp.467–479
- Chow, George, Eric Jacquier, Mark Kritzman, and Kenneth Lowry, 1999. Optimal portfolios in good times and bad. *Financial Analysts Journal*, 55(3), pp.65-73.
- Dasgupta, A., 2004. Financial contagion through capital connections: a model of the origin and spread of bank panics. *Journal of European Economic Association*, 2, pp. 1049-1084
- Dimsdale, N., 2009. The financial crisis of 2007–2009 and the British experience. *Oxonomics*, 4(1), pp.1–9.
- ECB, 2009. December. *Financial stability review*. Tech. rep. European Central Bank.

- Corsi, F. Lillo, F. Pirino, D. and Trapin, L., 2018. Measuring the propagation of financial distress with granger-causality tail risk networks. *Journal of Financial Stability*, 38, pp.18–36.
- Ghysels, E., 2017. MIDAS Matlab Toolbox, Version 2.2.
- Weiß, G.N. Neumann, S. and Bostandzic, D., 2014. Systemic risk and bank consolidation: international evidence. *Journal of Banking & Finance*, 40, pp.165-181.
- J.A. Chan-Lau, M. Espinosa, K. Giesecke, J.A., 2009. Sole assessing the systemic implications of financial linkages. *IMF Global Financial. Stability. Report*, pp. 73-110.
- Kleinow, J. Moreira, F. Strobl, S. and Vhmaa, S., 2017. Measuring systemic risk: A comparison of alternative market-based approaches. *Finance Research Letters*, 21, pp. 40-46.
- Kritzman, M. Li, Y. Page, S. and Rigobon, R., 2011. Principal Components as a Measure of Systemic Risk. *The Journal of Portfolio Management*, 37(4);
- Kritzman, M. and Li, Y., 2010. Skulls, financial turbulence, and risk management. *Financial Analysts Journal*, 66(5), pp.30-41.
- Lupu, R. Călin, A.C. Bobirca, A.B. and Miclăuș, P.G., 2018. Stock Market Fragility for Macroprudential Policies in Eastern European Countries. *Economic Computation and Economic Cybernetics Studies and Research*, 52(4), pp.19 – 33.
- Markose, S. Giansante, S. and Shaghghi, A.R., 2012. Too interconnected to fail financial network of US CDS market: Topological fragility and systemic risk. *Journal of Economic Behavior & Organization*., 83, pp.627-646.
- Moagar-Poladian, S. Folea, V. and Paunica, M., 2017. Competitiveness of EU member states in attracting EU funding for research and innovation. *Romanian Journal of Economic Forecasting*, 20(2), pp. 150-167.
- Papanikolaou, N. and Wolff, C., 2014. The role of on- and off-balance-sheet leverage of banks in the late 2000 crisis. *Journal of Financial Stability*, 14(1), pp.3–22.
- Rodríguez-Moreno, M. and Peña, J.I., 2013. Systemic risk measures: the simpler the better?, *Journal of Banking & Finance*, 37(6), pp.1817-1831.
- Saman, C., 2016. The Impact of the US and Euro Area Financial Systemic Stress to the Romanian Economy. *Romanian Journal of Economic Forecasting*, 19(4), pp.170-183
- Silva, W. Kimura, H. and Sobreiro, V.A., 2017. An analysis of the literature on systemic financial risk: A survey. *Journal of Financial Stability*, 28, pp. 91 – 114.
- Xu, Q. Chen, L. Jiang, C. and Yuan, J., 2018. Measuring systemic risk of the banking industry in China: A DCC-MIDAS-t approach. *Pacific-Basin. Finance Journal*, 51, October, pp.13-31.