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SPILLOVER EFFECTS AND LONG-TERM CORRELATIONS ON EUROPEAN FINANCIAL MARKETS

Abstract. *The academic literature in the field of financial stability has been developing intensively, especially after the last European financial crisis, spurring the development of various algorithms that spawned different statistical gauges. While many of these indicators gained traction within the industry both from the perspective of financial investors and from the regulators' angle, they are tailored to reveal different facets of the complex idea of stability. This paper investigates the extent to which the spillover measure constructed by Diebold and Yilmaz (2012) is impacted by the long-term component of dynamic conditional correlations computed with MIDAS DCC GARCH methodology. We apply this analysis to the sectoral indices that are components of the European STOXX 600 index and show the correlation pairs with the higher impact on the spillover index.*

***Keywords*:** spillover effects, contagion, dynamic conditional correlations, financial stability.

JEL Classification: D53, G15, G19

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1. Introduction

Financial stability confers to the financial system the resilience it needs to diminish, dissipate, or even absorb shocks and macroeconomic imbalances. In this respect, achieving a satisfactory degree of financial stability reduces the risks of disruption or poor functioning of the financial intermediation process. For this reason, it is important to identify the elements that reveal various facets of the complex idea of stability.

Since the global financial crisis, the concept of financial stability and the policies constructed to support it have undergone a profound rethinking process. Consequently, the regulatory mechanism entered in a reforming stage, with achieved results and still uncovered issues. As a result, the analysis of the financial stability intensified over the last years. A review and analysis of post-crises regulatory framework is dilated on by Aikman et al. (2018), Duffie (2017) or Financial Stability Board (2018).

To better reveal the mixt impact of micro and macroprudential tools, monetary policy and regulatory framework while detaching the individual influence and the transmission channel, new and more complex quantitative models are needed. In this regard, in the economic literature stand out some works that capture influences on an extensive scale.

For instance, Brunnermeier and Sannikov (2014) and Brunnermeier et al. (2012) included the financial frictions in the analysis of the economy's equilibrium, whilst Cont and Schaanning (2017) and Greenwood et al. (2014) studied the role of macroeconomic factors for "within-system feedbacks". The linkage between macroeconomy and the systemic risks is examined by Giglio et al. (2016) for Europe and US for few decades; they suggested a model for designing systemic risk indexes to anticipate shocks outside the sample.

Given the fact that correlations are linear measures of dependence, most efforts had been channelled to capture non-linear perspectives of these connections. The resulted measures rely on significant VAR coefficients (Diebold and Yilmaz 2012), the first components from a PCA methodology applied on large series of returns as in Kritzman et al. (2010) or multivariate measures of deviations from "normality" as presented by Kritzman and Li (2010).

Many of these indicators and their derivations became standard trackers that financial authorities employ in their attempt to capture early warning signals for financial instability events. In the same vein, our paper questions the extent to which these indicators depart form the realm of linearity that governs the measure of dependence and rely on measures of non-linearity, which is far more complex and may encapsulate several solutions to the same problem.

Our approach to elucidate in part this investigation embodies an analysis of the extent to which deviations from the long-term correlations between sectoral indices influence tendency of these indices to generate spillover effects.

To this end, we use MIDAS DCC GARCH models to obtain dynamic correlations and to compute deviations from these so-called secular components for each pair of sectoral indices and we investigate if they explain the spillover index.

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Namely, we calculate the dynamic correlations between these indices from European markets and extract the long-term component of the correlations with the MIDAS DCC GARCH methodology. The final objective would be to detect the contribution of correlations between sectors to the evolution of the spillover index.

In previous works, using different methodologies, we also investigated the correlation of the European stock markets (Lupu (2015)), the connexity between sentiment indices and stock markets' evolution (Lupu, Hurduzeu and Nicolae (2016)).

The rest of the article is organized as follows. A specific literature review is presented in the section two, while the section three is dedicated to data and methodology used for the current research. The obtained results are described in the section four, and the last section are formulated the main conclusions.

2. Review of the scientific literature

The issue of financial stability gained even more attention in the economic literature after the global financial crisis, when unprecedented effects and events availed a unique capably to encompass the new linkages and influences on the financial markets.

The European markets have specific features derived from the construction of the European Union where common interests correspond, but may also differ from national ones. Taking into account these characteristics, Schoenmaker (2011) proposed the "financial trilemma" that refers to "financial stability, financial integration and national financial policies", considering impossible to achieve them all in the same time, while any kind of two elements combinations being possible. At the European level, the building of the Capital Market Union is considered as a support for the financial stability (Panait (2015)).

The key weaknesses of the Economic and Monetary Union's architecture are presented and discussed by de Haan et al. (2014). Albeit the majority of this problems were somehow addressed by policy makers, the authors concluded that their success depends on implementations, coordination and risk sharing. A study that focused on compared volatilities on European stock market is Albu et al. (2015). Previous work in this field was also realized by Lupu (2014).

Billio and Caporin (2009) evidenced contagion for Asian and American stock markets using simultaneous equation system with GARCH errors methodology.

We identified studies that are looking at the relation financial volatility – economic activity from, the direction of the investigation being from financial market to economic fundamentals (Daly (2018)). Also, Albu et al. (2017) analyzed the industries associated with risk for European stock market.

There are some studies (Beltratti and Morona (2006), Cardarelli et al. (2011), Beetsma and Giuliodori (2012)) that on the base of empirical results educed the fact that after the global financial crisis, the contractionary influence was greater in banking industry comparing with stock and currency markets; the

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main conclusion of this category of studies is that the real economy seems to not be influenced by the stock market's volatility.

In the literature, several studies address the link between certain sectors of the economy and financial volatility or stability. The oil sector is one of most analyzed from this perspective. For instance, there are published some analysis focused on a group of countries that check over the linkage between the volatility of oil prices and stock markets for countries members of G7. Diaz et al. (2016) concluded that stock markets from these countries negatively react to a rising of oil price volatility, with a substantial higher influence from the global volatility, compared with the national ones. Another interesting approach is related with investigation of direction volatility transmissions. For the period 1991-2014, Nazlioglu et al. (2015) found that the spillover transmission was from oil price to the financial stress index before the global financial crisis and inverted after that.

This research is based on the methodology proposed by Diebold and Yilmaz (2012) that was improved or directly replicated by numerous other authors for different markets, periods and frequencies.

The same methodology (Diebold and Yilmaz (2012)) was used by Liow (2015) for G7 group of countries for the period January 1997 - December 2013; the results emphasize the toughness of the volatility in national stock markets, but the co-integration of their cycles is presumed by the "unobserved common shocks".

Diebold and Yilmaz (2012, 2014) was used to analyze the spillovers on the accessible and inaccessible stock markets, focusing on Asian markets. The main results discuss the major role of the international investor in markets' comovements and the intensifying function of the markets' openness for spillover effect.

Recently, Caloia et al. (2018) applied the same methodology for the euro zone stock market for the period 2000-2016, but modified it by replacing the stationary VAR with "long-memory behaviour of the series". The authors intended to catch the non-symmetrical conduct of investors regarding risk.

In other paper, Diebold and Yilmaz (2012) methodology is applied in parallel with the Barunik and Krehlik (2018) methodology for stocks, currencies, sovereign bonds and credit default swaps markets for the period between 2009 and 2016; the analysis for volatility spillovers across these four big markets brought different results, the last indicating a surpass connectivity for higher frequencies.

In other cases, Diebold and Yilmaz (2012) approach was used to improve other methodologies, like in the case of Chau and Deesomsak (2014) where Oet et al. (2011) methodology was modified with the newer one with the final scope to assess the financial stability by analyzing the transmission of the financial stress through the "Financial Stress Spillover Index" consider by the authors a good predictor for setting the financial crisis in a timeline.

3. Data and methodology

We employ Bloomberg data on historical values of the sectoral components of STOXX 600 index from January 2010 until February 2019, totalizing 2378 daily

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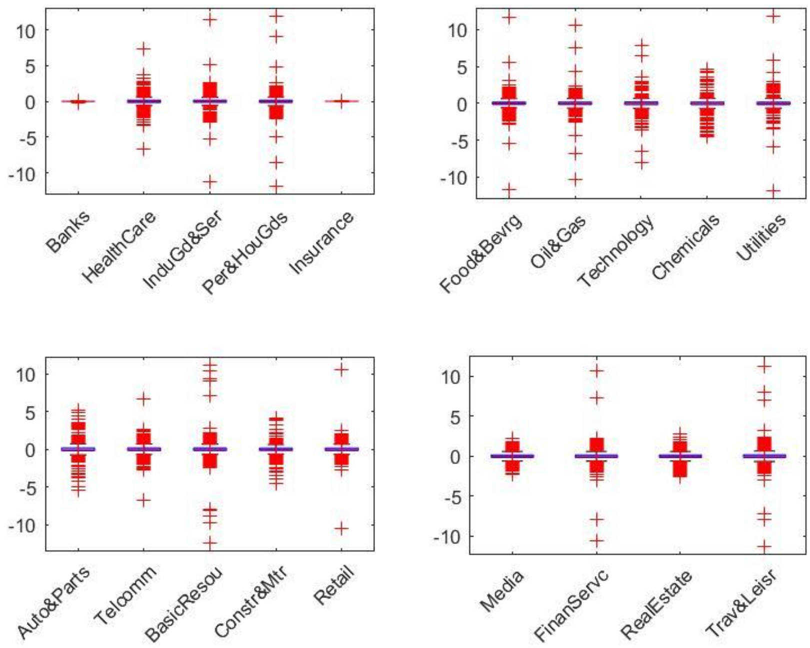
observations, for 19 sectors. Figure 1 exhibits boxplots for the daily log-returns for each of these indices.

Figure 1 - Statistical properties of log-returns



Source: Authors' computation

We notice very low variation in the case of Banks and Insurance and several deviations from the mean especially for Basic Resources, Travel and Leisure and Utilities. Given these distributional properties, we expect our analysis to reveal different contributions to the spillover index from these sectoral log-returns. The Financial Services sector feature a rather large volatility, with several outliers, especially when compared with the Banks and Insurance sectors.

In terms of methodology, we rely on two streams of research that investigate the evolution of spillover for a system of financial variables on one hand and the dynamics of correlations for a set of financial assets on the other hand.

In order to understand the contribution of sectors to the spillover phenomenon, we will consider the nineteen sectoral indices as components of a financial system that has the tendency to exchange impacts and information from one sector to another.

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We compute the spillover index based on the work developed by Diebold and Yilmaz (2012), DY onwards. As such, in a VAR setting they consider the error variances in forecasting the homogenous variables as informative to separate between two types of influences: the contribution of a shock in variable x_i to the forecast error of x_i and the contribution of shocks to another homogenous variable x_j that affect forecasting of the same variable x_i. DY monitor the several number of steps ahead for error variances in forecasting and disentangle *cross variance shares* as a measure for spillovers.

DY developed the variance decomposition of the forecast error as:

$$VD_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h A_h' e_i\right)}$$

where H is the number of steps ahead for the forecast, Σ denotes the variance matrix for the error vector ϵ, σ_{ii} represents the standard deviation of the error term for the ith equation in the VAR system and e_i is a vector with one as the ith element and zeros in all the other situations. Further, DY normalize each entry of the variance decomposition matrix in the following manner:

$$\widetilde{VD}_{ij}^{g}(H) = \frac{VD_{ij}^{g}(H)}{\sum_{j=1}^{N} VD_{ij}^{g}(H)}$$

As consequence, by employment of the volatility contributions from the variance decomposition, the spillover index is

$$SI^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \widetilde{VD}_{ij}^{g}(H)}{N} \times 100$$

For the evolution of correlations, we rely on the work of Colacito et al. (2011). They consider that log-returns follow the stochastic process that describes the GARCH-MIDAS model:

$$r_{it} = \mu + \sqrt{\tau_t g_{it}}\,\epsilon_{it}$$

where g_{it} represents the dynamics of the variance and it is governed by the following rule:

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$$g_{it} = (1-\alpha-\beta) + \alpha \frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}$$

The evolution of the volatility is modeled so that we can observe a long-term component. In the standard GARCH(1,1) specification, the unconditional variance in specified by the $(1-\alpha-\beta)$, which is constrained to be positive. Under this specification the of τ_t takes care of the dynamics of the long-term component:

$$\tau_t = m + \theta \sum_{k=1}^{K} \psi_k(\omega) V_{t-k}$$

where by V_t we denote the realized variance, i.e. $V_t = \sum_{i=1}^{N} r_{it}^2$, while $\psi_k(\omega)$ are the Beta weights from Engle et al. (2006), defined as $\psi_k(\omega) = \frac{\left(1-\frac{k}{L}\right)^{\omega-1}}{\sum_{j=1}^{L}\left(1-\frac{j}{L}\right)^{\omega-1}}$.

From this specification, Colacito et al. (2011) developed the DCC-MIDAS in two steps: firstly, we assume that the variances follow a GARCH-MIDAS model and secondly, we consider that a quasi-correlation matrix, Q_t changes over time. The element of this correlation matrix obeys the law:

$$q_{it} = \rho_{ijt}(1-a-b) + a\epsilon_{i,t-1}\epsilon_{j,t-1} + bq_{ij,t-1}$$

The long-run component ρ_{ijt} is the MIDAS weighted-sum of the sample correlation matrices

$$\rho_t = \sum_{k=1}^{K} \psi_k(\omega) c_{t-k}$$

The correlation matrix that evolves with time is computed by rescaling the quasi-correlation matrix (that has elements q_{it}) so that the diagonals are unity, i.e.

$$Corr_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}}$$

As previously mentioned, we compute both the spillover index and the DCC-MIDAS correlation matrix for the log-returns of the nineteen sectoral components of STOXX 600. After the extraction of the long-term component in the correlations, we compute the differences of correlations with respect to these

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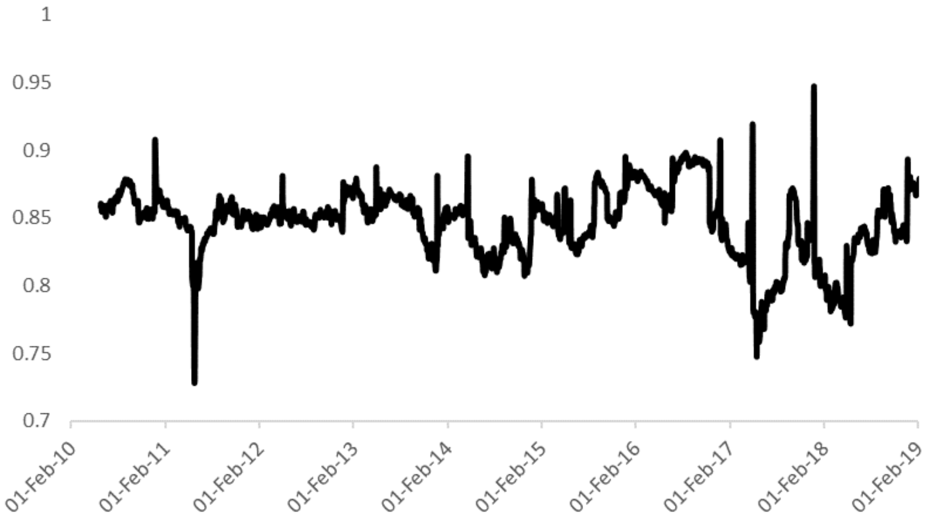
components. We average these values across each sectoral component and the obtained variable is used as explanatory in a regression where the dependent variable is the spillover index.

4. Results and discussion

` The first step in our analysis consists in the estimation of the spillover index according to Diebold and Yilmaz (2012)[1]. We employed all the sample of nineteen sectoral indices for which we applied the VAR procedure sequentially for samples of 100 observations. We recorded the value of the spillover index for each sample and created the chart in Figure 2.

Figure 2 - Evolution of the Spillover Index for the STOXX 600 components



Source: Authors' computation

An analysis of this evolution shows that the values of the spillover index tend to be rather stable, moving around the mean of approximately 0.85, which could be considered as the regular market conditions. We notice several episodes of large spikes especially in the last quarter of our sample, i.e. from 2016 onwards. The negative trend during 2017, disturbed by a spike at mid-year, constitutes a reflection of the calm period on stock markets during that time and is correlated with an increase in the global market indices. However, connections of this index with the global events that trigger stock market movements should be considered with particular care as this index reflects the extent to which one sector has the

[1] We employed the Matlab code developed by Ken Nyholm from the European Central Bank.

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tendency to push influences on the other sectors, which means that the general stylized facts of log-returns are not necessary features of this index.

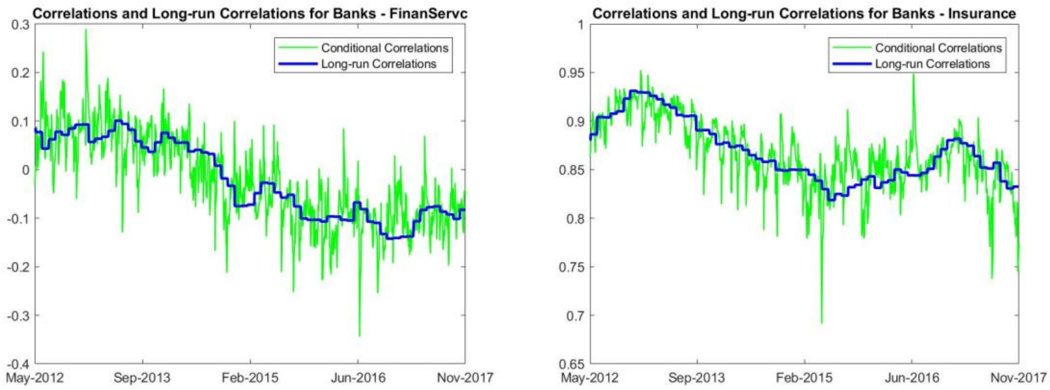
However, the upward trend after February 2018 corresponds to the general increase in volatility in the global markets for this period. Moreover, this trend starts with a sharp increase in February 2018, which is the moment when global markets experienced stark negative jumps and important volatility shocks as result of speculation on financial instruments that bet on reduced volatility.

The second step in our analysis consists in the application of the MIDAS-DCC methodology on the log-returns of the sectoral indices[2]. For this analysis we computed a 19 x 19 matrix of correlations for each day in our sample.

As mentioned in the previous section, this approach necessitates two stages: the first stage deals with the computation of the MIDAS-GARCH for each series, which yields 19 vectors of volatilities and their long-term components, while the second stage consists in the estimation of all pairs of correlations together with their corresponding "secular" components. This generated 171 vectors of daily correlations and another set of 171 long-term components for each of these pairs.

Given their large number, we decided to show in Figure 3 the evolution of the correlations of the Banking sector with the Financial Services, Insurance, Basic Resources and Media.

Figure 3 - Evolution of dynamic correlations and their secular components for selected pairs



[2] The estimation of MIDAS-DCC was realized by using the Matlab code developed by Eric Ghysels, MIDAS MATLAB Toolbox, version 2.2

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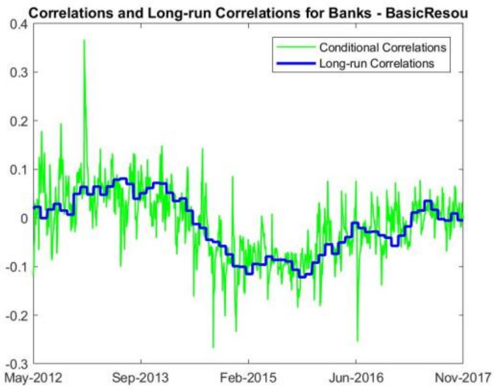

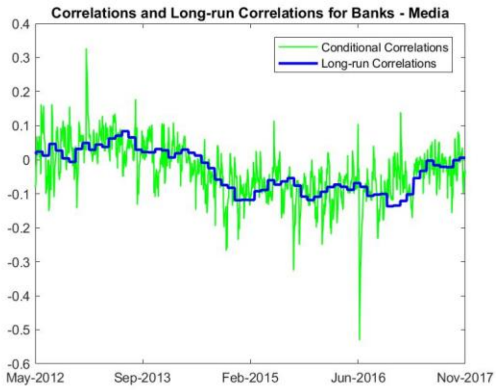

Source: Authors' computation

We notice that the long-term components have similar tendencies, with a clearer downward trend for the evolution of correlations of Banks with the Insurance sector and without clear trends for the correlations with the Media. We can observe though that the connections with the Insurance sector is highly positive, reaching increased levels at times, while with the other sectors we notice that correlations are also negative.

One other aspect with more importance for our analysis is the extent to which the daily correlations tend to depart from the long-term component. We notice, for instance, that the volatility of the dynamic correlations is quite reduced in the case of Banks-Insurance pair (notice the scale in the y axis), which means that when correlations are large, they also tend to be quite stable in time.

In consequence, as mentioned in the previous section, we compute the deviations from these long-term components for all pairs in our sample, which generated a series of 18 such deviations for each sectoral index. Computing averages across each day for the absolute values of these deviations, we obtained 18 mean absolute deviations, one for each index. Figure 4 depicts the dynamics of these deviations across time and sectors.

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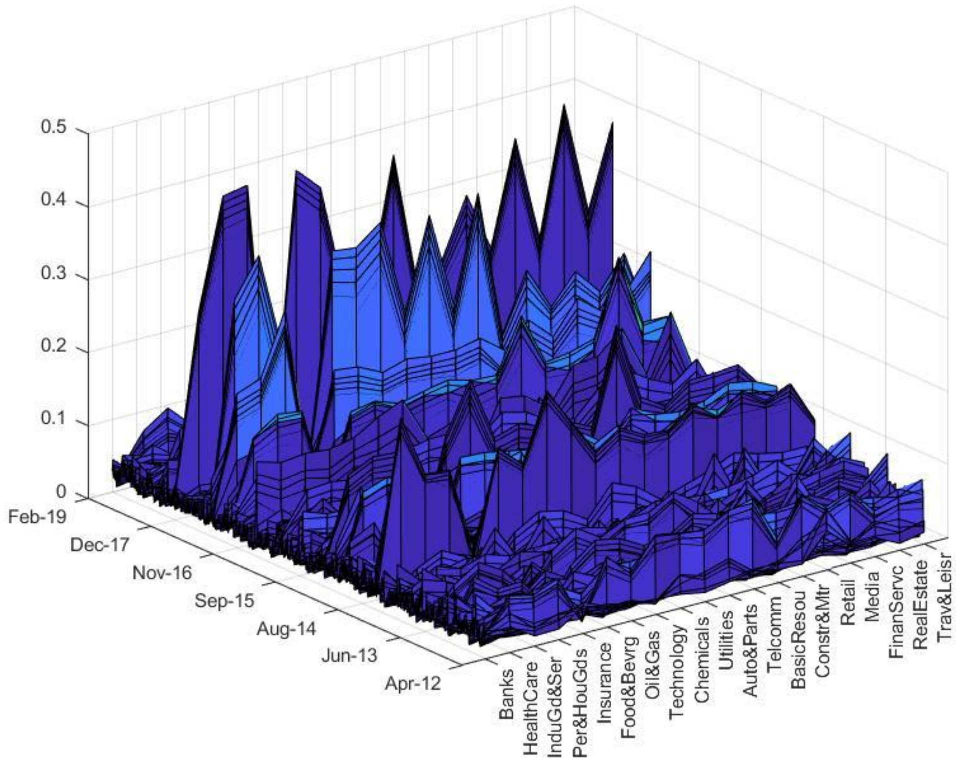
Figure 4 - Evolution of average deviations from secular trend in dynamic correlations



Source: Authors' computation

One interesting element in the evolution of these deviations is the fact that they show a rather increased trend for most sectors towards the end of the sample, which shows that correlations tend to be more volatile as time passes. This in turn is also an argument in support of the fact that the long-term component is more uncertain towards the end of the sample.

In order to provide answers concerning the non-linear implications of correlations among sectoral components, we looked at the possible connections between these deviations from the secular components and the dynamics of the spillover index.

In pursuit of this investigation, we ran a set of simple regressions between the spillover index, as dependent variable and the set of deviations of correlations from their long-term components as explanatory variables. We exhibit the results of these regressions in Table 1.

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Table 1: Regression results for spillover index on dynamic deviations from secular trends in correlations

	Coefficients	Standard Errors	t-Stats	p-Values
Banks	0.0386	0.0087	4.4351	0.0000***
HealthCare	0.0129	0.0068	1.9026	0.0572*
InduGd&Ser	0.0019	0.0068	0.2845	0.7760
Per&HouGds	0.0091	0.0067	1.3452	0.1787
Insurance	0.0372	0.0086	4.3432	0.0000***
Food&Bevrg	0.0082	0.0068	1.2088	0.2269
Oil&Gas	0.0061	0.0074	0.8216	0.4114
Technology	0.0073	0.0075	0.9694	0.3324
Chemicals	0.0118	0.0072	1.6351	0.1022
Utilities	-0.0017	0.0075	-0.2307	0.8176
Auto&Parts	0.0101	0.0082	1.2314	0.2183
Telcomm	0.0000	0.0081	-0.0053	0.9958
BasicResou	0.0235	0.0080	2.9257	0.0035***
Constr&Mtr	0.0145	0.0074	1.9513	0.0511*
Retail	0.0164	0.0086	1.9081	0.0565*
Media	0.0164	0.0079	2.0685	0.0387**
FinanServc	0.0121	0.0076	1.5926	0.1114
RealEstate	0.0165	0.0079	2.1040	0.0355**
Trav&Leisr	0.0197	0.0086	2.3007	0.0215**

Source: Authors' computation

We notice that almost half of the regressions provided significant results up to 90% level of confidence. We found that Banks, Insurance and Basic Resources gave us the most significant situations in which deviations from the long-term components have the tendency to influence the evolution of spillovers across sectors in Europe.

We connect this findings we the fact that several analyses revealed the central importance of the financial industry (banks and insurance companies) as the main influencers for general financial stability. The companies that are part of the Banking and Insurance sectors are the ones considered systemically important financial institutions and are closely monitored by regulatory bodies.

The fact that deviations from correlations with the rest of the sectors are influencing the potential to affect the rest of the system is a proof that the dynamics of the stock prices for the traditional representatives of the financial system are still considerably important for the evolution of financial stability.

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5. Conclusions

Financial stability tracked increasing attraction after the burst of the last global financial crisis. Phenomena previously described by academia resurged with high intensity in the aftermath. One such feature is the financial contagion, felt with great speed as the crisis unfolded. Seen as the downside of financial integration, the contagion phenomenon spurred a great deal of academic literature especially after the Asian crisis in 1997. Several such gauges had the main objective to exploit a well-advertised stylized fact, i.e. that correlations are changing and they tend to increase mostly when prices decrease (i.e. when returns become negative).

Given the large body of literature generated by the attempt to develop indicators needed to monitor the evolution of the financial system, regulatory authorities need a closer look at the relations among these gauges.

To this end and given the fact that financial stability phenomena tend to propagate in non-linear manners, the objective or our paper is to analyze the extent to which the spillover index of Diebold and Yilmaz (2012) is influence by the volatility of correlations for the nineteen sectoral indices that compose the STOXX 600 capital index.

Employing a MIDAS-DCC methodology we showed that the deviations of correlations from their secular components explains the evolution of the spillover index especially for Banks and Insurance industries, which is supported by previous research and provides a framework for the development of other measures that could capture these non-linear features of financial stability indicators.

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