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RISK GENERATING INDUSTRIES FOR EUROPEAN STOCK MARKETS

Abstract. *The analysis of contagion received a substantioanl dose of academic attention. This paper aims to determine the potential contagion effects for a large set of financial assets. We employ 5-minute closing prices for the companies included in STOXX600 and build a methdological framework that allows the computation of simple differences between the Cornish-Fisher VaR and the standard normal distribution VaR dynamics. These differences account for the amount of risk that is generated by the non-normality of the distribution of log-returns, more precisely the part that is spurred by the skewness and kurtosis indicators. These measures are synthesized at industry level and submitted to a causality analysis. Our approach allows us to pinpoint possible inter-industry spillover effects and we find the industries that have the propensity to inject risk in the system via a Granger-causality test.*

Keywords contagion, systemic risk, Cornish-Fisher expansion, European Stock Markets.

JEL Classification G15, G31

1. Introduction

Financial literature has dedicated a solid interest to the investigation of the comovements observed on the markets. Conventional wisdom assumes that these comovements have grown in magnitude due to the proliferation of market integration.

In addition to market integration, these common patterns may be attributed to contagion. Financial contagion is defined by the tendency of asset prices to present an excessive dose of cross-market interdependence during times of economic turbulence.

The recent financial crisis underlined the vast linkages among financial institutions and the speed and depth of contagion propagation. Financial shocks, losses, defaults, insolvency or liquidity disturbances proliferated among institutions, industries, markets and countries. Moreover, Phylaktis and Xia (2009) argue that in times of crisis, market dynamics is even more related. This phenomenon was visible for all the major recent crises and holds a fundamental importance for all parties implicated in the financial system.

The interconnected character of financial markets explains the buildout of risk throughout the financial system and justifies the existence of regulatory frameworks. In addition to these, a relevant block of literature focused on the sources, symptoms, channels and dynamics of systemic risk. Despite these previous efforts, far less attention has been oriented towards determining the place of the structure of markets in generating systemic risk and contributing to fragility.

In this paper we aim to determine which industries have the potential of generating systemic risk and which industries have the tendency of absorbing it. Building on intraday data for the companies included in the STOXX600 index we compute the Cornish-Fisher VaR and determine the daily differences between the Cornish-Fisher VaR and the classical VaR. We ogranize the companies by industry and obtain 24 sets. In order to secure a measure of spillover effect among industries, we apply a Granger causality test on these average differences.

The remainder of this article is organized in the following way. Section 2 deals with a brief review of the precedent literature. Section 3 presents data selection and the methodological structure, while section 4 discusses the results. Section 5 concludes.

2. Review of the scientific literature

Early contributions on the idea of contagion focus on the ways in which shocks that happen in one country are relayed to others and in general consider a correlation approach. King and Wadhwani (1990) use intraday data for 1987 and observe an increase in cross-market correlation after the United States crash for US, UK and Japan. Calvo and Reinhart (1996) deal with developing countries and demonstrate that correlations in terms of equity prices between Asia and Latin America have greatly risen in concordance to the Mexican crisis of 1994. More contributions on this line can be traced back to Eichengreen, Rose and Wyplosz (1996), Baig and Goldfajn (1999) or Bertero and Mayer (1990).

This correlation approach is questioned by a seminal paper introduced by Forbes and Rigobon (2002). In a heteroscedasticity adjusted environment, the authors refute the idea of contagion for three different crises and advocate on the principle of interdependence. A vast and voluminous literature follows the specifics of contagion for different crises and various assets classes, generating relevant contributions among which we mention: Boschi (2005), Bekaert, Harvey and Ng (2005), Boyer, Kumagai and Yuan (2006), Dungey Milunovich and Thorp (2010), Longstaff (2010), Guo, Chen and Huang (2011), Beirne and Gieck (2012) or Dimitriou and Simos (2013).

More recently, Kenourgios and Dimitriou (2015) study contagion during the last global crisis for a wide set of both developed and emerging economies. They report that contagion was first visible in financial sectors and then moved towards non-financial ones.

Akther and Daly (2017) report that potential negative shocks occurring for systemically relevant banks can influence Australian banks. Using logit regression models the authors forecast possible transmissions of shocks in the distance to default and advocate in favor of prudential regulations.

Roy and Roy (2017) aim to determine the potential contagion effects among the gold, government bond, stock and foreign exchange markets and the commodity derivative market for the case of India. They use daily returns for the 2005 – 2015 period and a DCC-MGARCH approach. They report that the highest contagion is found for the pairing of the commodities market with the gold market, while the lowest effects are observed for the case of the bond market.

In a very recent contribution with much relevance for the present paper, Fry-McKibbin et al (2017) develop a novel class of joint test for contagion. The distinguishing feature of this approach is that it studies contagious relations by means of higher order comoments. The authors thus focus on coskewness, cokurtosis and covolatility in their investigation on contagion. The empirical tests are calibrated for the subprime crises, the great financial crisis and the European debt crises and demonstrate solid higher order contagion in terms of comoments.

Our paper relates more profoundly to those contributions which sought to determine de presence of contagion for various sectors or industries.

For instance, Phylaktis and Xia (2009) investigate sectoral contagion for 10 sectors in 29 markets from Europe, Asia and Latin America for the January 1990 – June 2004 interval. The authors regard contagion as an excessive correlation and use the specification provided by Bekaert, Harvey and Ng (2005). They document on an aggregate contagion for the entire sample for the vast majority of sector from Europe, Asia and Latin America. Despite this fact, Phylaktis and Xia (2009) highlight the differences in terms of transmission channels.

Shahzad et al (2017) consider contagion for the US industry-level credit markets. Using data with daily frequency for the December 2007 – December 2014 period and a wavelet framework, the authors show that the “Basic Materials” industry credit market presents the highest interdependence with the rest of the set. Contrary results are reported for “Utilities”.

3. Data and methodology

The Cornish-Fisher expansion translates into a measure of VaR which considers the distributions of the assets’ prices or returns that are not normal. Moreover, the Cornish-Fisher expansion accomodates portfolio optimization with a measure of risk that is more refined than variance such as VaR or even Conditional VaR. The original specification found in Cornish and Fisher (1937) builds in the dirrection of an easier procedure to account for higher moments in the distributions of prices and returns. In other words, the Cornish-Fisher expansion points to a clear relation between the skewness and kurtosis parameters and the normal and conditional variance, being a tractable solution for mean-VaR or mean C-VaR optimizations (Cao, Harris and Jian, (2010)).

The Cornish-Fisher approach can be summarized in the following mathematical setup:

$$CF^{-1}(\mathrm{p}) = \phi_p^{-1} + \frac{y_1}{6}((\phi_p^{-1})^2) + \frac{y_2}{24}((\phi_p^{-1}))^3 - 3\phi_p^{-1} - \frac{y_1^2}{36}(2(\phi_p^{-1})^3 - 5\phi_p^{-1})$$

Where:

y_1 reprents kurtosis

y_2 stands for the excess kurtosis of the standardize returns and

ϕ^{-1}(p) is the standard normal distribution

This paper employs intraday data collected from Bloomberg for the 1 September 2016-16 March 2017 time interval. The data represent closing prices for 600 European companies included in the STOXX600 index, observed with 5-minute frequency for the trading day starting from 7:00 and ending at 15.35. In the cases in which prices were not recorded for the 5-minute interval, the return was considered to be zero. We removed the companies with insuficient data, obtainig a set of 573 companies. Figures 1 and 2 present a synthetic image of several samples extracted from the data set. Starting from these intraday postions we computed daily returns.

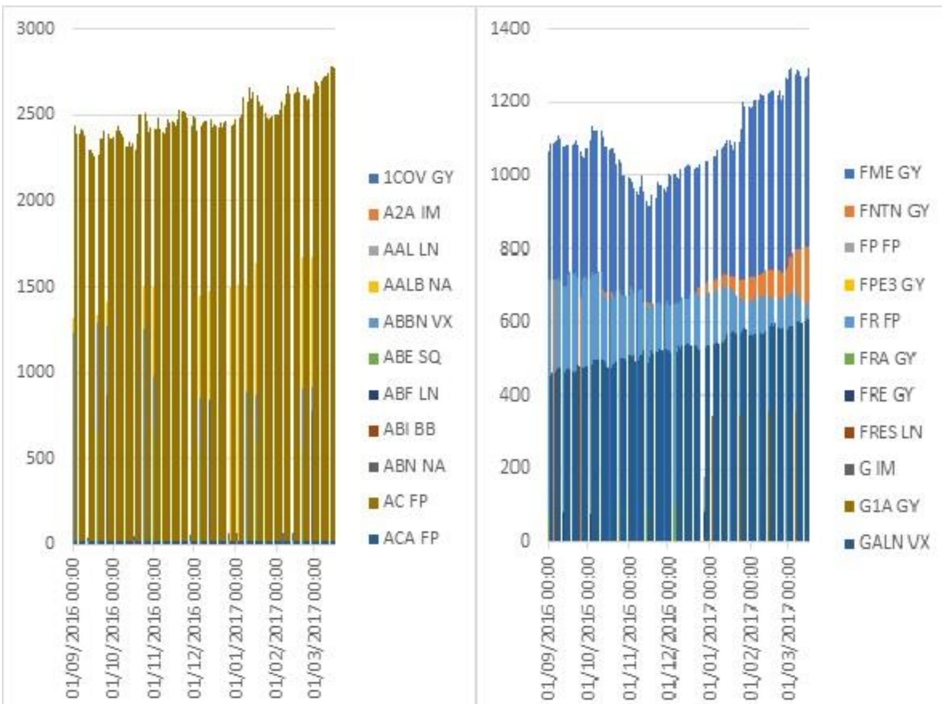
The first step in our approach consisted in the computation of the daily variance and the skewness and kurtosis coeficients in order to be able to employ the Cornish-Fisher expansion. According to Barndorff-Nielsen and Shephard (2003), we use realized measures for the variance, skewness and kurtosis coefficients.

We compute the realized daily variance by summing up the squared returns:

$$\text{RDVar} = \sum_{n}^{i=1} r_{t,i}^2$$

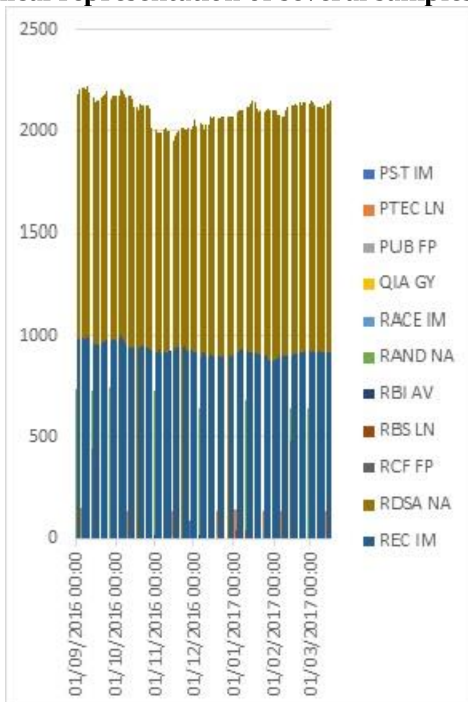
These values were used to compute the standardized returns so that we can use them in the Cornish-Fisher formula and further back to compute the Cornish-Fisher VaR.

Figure 1. The graphical representation of several samples from the input data



Source: Autors' computation

Figure 2. The graphical representation of several samples from the input data



Source: Autors' computation

We then compute the realized daily skewness and kurtosis using th following relations:

$$RDSkew_t = \frac{\sqrt{N}\sum_{i=1}^{n} r_{t,i}^3}{RDVar_t^{\frac{3}{2}}}$$

$$RDKurt_t = \frac{N\sum_{i=1}^{N} r_{t,i}^4}{RDVar_t^2}$$

After this step we are able to compute the Cornish-Fisher VaR, according to the following mathematical setup:

$$VaRCF_t^{0.01} = -\sigma_{i,t} CF^{-1}(0.01)$$

where i is the asset, i.e. the 573 companies in our sample and t is the day for which we compute the VaR and $\sigma_{i,t}$ is the realized volatility, i.e. $\sqrt{RDVar_t}$. $CF^{-1}(0.01)$ is the Cornish-Fisher expansion computed for the probability of 0.01.

This VaR measure will be compared with the classical VaR, in which we use the same volatility measure $\sigma_{i,t}$. Therefore

$$VaR_t^{0.01} = -\sigma_{i,t}\phi_{0.01}^{-1}$$

We compute the daily differences between the Cornish-Fisher VaR and the classical VaR ($VaRCF_t^{0.01} - VaR_t^{0.01}$) and we group the companies by industry to obtain 24 sets. For each set we determine the daily average for the above mentioned difference. We interpret these differences as measures of the amount of risk that is provoked by the extent to which the distributions of these variables deviate from normality, i.e. the amount of fatness in the left tail as measured by skewness (usually negative in the case of equity log-returns) and kurtosis.
In order to obtain a measure of spillover effect among industries, we apply a Granger causality test on these average differences. Focusing on these causality patterns we then set off to quantify which are the industries that can have the greatest contribution in terms of adding systemic risk.

4. Results and discussion

As previously stated, the last part of our methodology focuses on a Granger causality approach which permits the observation of the potential relationship that exist between industries for all the posibile industry combinations. We notice statistically significant effects in 122 cases out of the total number of possible combinations. The first pair from the analysis discusses the potential relations between the banking industry and the one dedicated to the construction of automobile and components. For this set of industries, the first side of the null hypothesis states that the banking industry does not Granger cause the Automobile and components industry. Besides this, the null hypothesis later statest that the automobile industry does not Granger cause the banking industry. For the first side we notive a probability value of 0.9833. This is above the 0.05 benchmark and therefore we can’t reject the null hypothesis. Morevover, we next observe a p-value of 0.6157. This is again above the threashold of 0.05, and therefore we can’t establish a causality relation between the two industries.

Given the great number of observations, from this point onward, the comentary will focus soley on those cases for which we detected a statistical significant causality. The first pair with significance links up the folowing two industries: Commercial & Professional Services and Automobiles & Components. The p value for the null hypothesis stating that the automobile industry does not Granger cause Commercial & Professional Services is 0.0000000000003 which is below the significance benchmark. In this case we reject the null hypothesis and notive the causality relations leading from Automobiles & Components to Commercial & Professional Services.

The second pair for which we record statistically significant results is the binom of Automobiles & Components and Consumer Services. For this case we obtain again a very low probability (0,0000000001) hinting to the fact that Automobiles & Components Granger causes Consumer Services. Following the Automibiles & Components industry we notice that it also Granger causes Food Beverage and Tobacco, Health Care Equipment, Household Personal Products, Insurance, Materials, Media, Pharmaceuticals, Biotechnology & Life Sciences, Retailing and Software & Services. In total, it manages to cast an influence on 12 industries which accounts 50% of our indurstry sample.

Focusing on Diversified Financials we observe that it Granger causes the following set of industries: Automobiles & Components, Capital Goods, Consumer Services, Tehnology and Hardware and EQ. Moving forward with the detected effects we notice the fact that the Banking industry Granger causes: Semiconductors, Software & Services, Transportation. We determine a strong reaction from Transportation in the sense that it casts its influence on the folowing industries: Energy, Insurance, Materials, Retailing, Semiconductors & Semiconductor Equipment, Software & Services, Tehnology and Hardware and EQ, Telecommunication Services and Utilities. We also notice that Telecomunication services is succesful in Granger causing a wide set of industries such as: Energy, Semiconductors & Semiconductor Equipment, Software & Services, Tehnology and Hardware and EQ, Transportation and Utilities.

We obtain statistical relevant results hinting to the idea of Granger causality for the vast majority of industries included in the analys. In addition to this, we isolate instances of bi-directional Granger causality. These cases are shown in Table in Appendix 1.

As previously stated, after determining the above mentioned causality patterns we aim to gauge which are the industries that could contribute the most in the proliferation of the possible effects of systemic risk. We thus focus on the industries with the largest number of instances in which they Granger cause another industry. We notice that Automobiles and Components, Software & Services and Transportation have the highest impact on the data set, numbering each 10 cases of Granger causality with other industries. This group is closely followed by another batch of high-impact industries such as: Semiconductors & Semiconductor Equipment, Technology Hardware & Equipment, Utilities and Telecommunication Services. At the opposite spectrum, the industries with the lowest potential in the proliferation of systemic risk are: Banks, Food Beverage & Tobacco, Media, Consumer Services, and Materials.

Table 1 shows the ranking for the top risk generating industries, while Table 2 represents the ranking for the industries that are the most frequent receivers of influence.

Table 1: Top risk generating industries

Rank	Industry
1	Automobiles and Components
2	Software & Services
3	Transportation
4	Semiconductors & Semiconductor Equipment
5	Technology Hardware & Equipment

Source: Autors' computation

Table 2: Top receiving industries

Rank	Industry
1	Transportation
2	Utilities
3	Semiconductors & Semiconductor Equipment
4	Energy
5	Telecommunication Services

Source: Autors' computation

5. Conclusions:

We conducted an analysis on possible contagion effects for the industries that defined by the companies from Stoxx 600. Using prices with 5-minute frequencies for these companies, our methodology presents an algorithm that leads to simple differences between the Cornish-Fisher and VaR dynamics. We aggregate these differecens industry-wise and aim to isolate potential contagion chanells. We determine causality patterns and notice that the industries capable of criystallising the most risk are: Automobiles and Components, Software and Services, Transportation, Semiconductors and Semiconductor Equipment, Technology Hardware and Equipment.

On the other hand, we manage to isolate the industries that absorb the most amount of risky influnces introduced on the market. These are: Transportation, Utilities, Semiconductors and Semiconductor Equipment, Energy, Telecommunication Services.

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Appendix 1

Bi-directional Granger causality

1	FOOD_BEVERAGE___TOBACCO vs AUTOMOBILES___COMPONENTS
	AUTOMOBILES___COMPONENTS vs FOOD_BEVERAGE___TOBACCO
2	HEALTH_CARE_EQUIPMENT___ vs AUTOMOBILES___COMPONENTS
	AUTOMOBILES___COMPONENTS vs HEALTH_CARE_EQUIPMENT___
3	FOOD___STAPLES_RETAILING vs CAPITAL_GOODS
	CAPITAL_GOODS vs FOOD___STAPLES_RETAILING
4	SOFTWARE___SERVICES vs CAPITAL_GOODS
	CAPITAL_GOODS vs SOFTWARE___SERVICES
5	UTILITIES vs CONSUMER____DURABLES_APP
	CONSUMER____DURABLES_APP vs UTILITIES
6	SEMICONDUCTORS___SEMICON vs ENERGY
	ENERGY vs SEMICONDUCTORS___SEMICON
7	TRANSPORTATION vs ENERGY
	ENERGY vs TRANSPORTATION
8	TRANSPORTATION vs MATERIALS
	MATERIALS vs TRANSPORTATION
9	TECHNOLOGY_HARDWARE___EQ vs RETALING
	RETALING vs TECHNOLOGY_HARDWARE___EQ
10	TELECOMMUNICATION_SERVIC vs RETALING
	RETALING vs TELECOMMUNICATION_SERVICES
11	TRANSPORTATION vs RETALIING
	RETALING vs TRANSPORTATION
12	UTILITIES vs RETALING
	RETALING vs UTILITIES
13	SOFTWARE___SERVICES vs SEMICONDUCTORS___SEMICON
	SEMICONDUCTORS___SEMICON vs SOFTWARE___SERVICES
14	TECHNOLOGY_HARDWARE___EQ vs SEMICONDUCTORS___SEMICON
	SEMICONDUCTORS___SEMICON vs TECHNOLOGY_HARDWARE___EQ
15	TELECOMMUNICATION_SERVIC vs SEMICONDUCTORS___SEMICON
	SEMICONDUCTORS___SEMICON vs TELECOMMUNICATION_SERVIC

16	TRANSPORTATION vs SEMICONDUCTORS___SEMICON
	SEMICONDUCTORS___SEMICON vs TRANSPORTATION
17	UTILITIES vs SEMICONDUCTORS___SEMICON
	SEMICONDUCTORS___SEMICON vs UTILITIES
18	TECHNOLOGY_HARDWARE___EQ vs SOFTWARE___SERVICES
	SOFTWARE___SERVICES vs TECHNOLOGY_HARDWARE___EQ
19	TELECOMMUNICATION_SERVIC vs SOFTWARE___SERVICES
	SOFTWARE___SERVICES vs TELECOMMUNICATION_SERVIC
20	TRANSPORTATION vs SOFTWARE___SERVICES
	SOFTWARE___SERVICES vs TRANSPORTATION
21	UTILITIES vs SOFTWARE___SERVICES
	SOFTWARE___SERVICES vs UTILITIES
22	TELECOMMUNICATION_SERVIC vs TECHNOLOGY_HARDWARE___EQ
	TECHNOLOGY_HARDWARE___EQ vs TELECOMMUNICATION_SERVIC
23	TRANSPORTATION vs TECHNOLOGY_HARDWARE___EQ
	TECHNOLOGY_HARDWARE___EQ vs TRANSPORTATION
24	UTILITIES vs TECHNOLOGY_HARDWARE___EQ
	TECHNOLOGY_HARDWARE___EQ vs UTILITIES
25	TRANSPORTATION vs TELECOMMUNICATION_SERVIC
	TELECOMMUNICATION_SERVIC vs TRANSPORTATION
26	UTILITIES vs TELECOMMUNICATION_SERVIC
	TELECOMMUNICATION_SERVIC vs UTILITIES
27	UTILITIES vs TRANSPORTATION
	TRANSPORTATION vs UTILITIES

Source: Autors' computation