Systemic Risk and Measures of Risk Spill-Over in the Financial System – The Case of Poland

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Abstract The recent global financial crisis has emphasized the importance of connectedness as a key dimension of systemic risk. Systemic risk is involved in the financial system, a collection of interconnected institutions that have mutual relationships through which losses can quickly propagate in periods of financial distress. In this paper delta CoVaR and the principal components analysis (econometric method to capture this connectedness) are applied to evaluate systemic risk in the financial system. The authors use the principal components analysis to estimate the number and importance of common factors the rates of return of selected companies in the financial sector (not only banks). The empirical study was conducted in the period from November 2004 until November 2018 with the purpose to investigate risk spill-over in the Polish financial system.

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1 Introduction to Systemic Risk

Systemic risk is a very complex issue to measure and "one of the most elusive concepts in finance" (Benoit et al., 2013, p. 22). Systemic risk may be understood as (Hansen, 2013, p. 4–5)

- a contemporary equivalent of a bank run, which is triggered by liquidity concerns,
- vulnerability of the financial network in which adverse consequences of internal shocks spread and/or magnify within the network itself, and
- the potential insolvency related to a major player in a component of the financial system.

Therefore, systemic risk could be driven by three main risk characteristics: liquidity risk, fragility of financial institutions and risk spill-over (Karaś, 2018). Benoit et al. (2013, p. 1) declare that "one-factor linear models explain most of the variability of the systemic risk estimates, which indicates that systemic risk measures fall short in capturing the multiple facets of systemic risk". Additionally, they also notice that different systemic risk measures have different focus and capture only a part of potentially crucial information about systemic risk.

In this paper the authors focused on the phenomenon of risk spilling over (as a part of systemic risk) from affected companies to the ones in a relatively good financial condition. The researchers are still looking for measures which will allow them to encompass all dimensions of systemic risk, and which are supplementary to these used by the regulators. Finally, they are searching for such measures which will result in obtaining non-replicated information. So far, no measure of systemic risk may be regarded as the best and the most appropriate one.

In the paper the authors selected two tools to identify the risk spill-over: The Delta CoVaR measure and the principal component analysis (PCA) method. The authors formulated two hypotheses. The first hypothesis stipulates that delta CoVaR and PCA are proper tools to identify risk spill-over in the Polish financial system. In order to verify it, the authors investigated availability and dependability of data together with various methods. The second hypothesis states that delta CoVaR and PCA as tools to identify risk spill-over provide the same conclusion. It was necessary to compare both measures and investigate whether they have the same focus and the same capture of potentially crucial information about risk spill-over. The empirical research related to systemic risk in the Polish financial system is conducted by the Central Bank for Poland (NBP) and other researchers, e.g. Karkowska (2015), Jajuga et al. (2017), Karaś and Szczepaniak (2017) or Karaś (2018).

Such an empirical study concerns the Polish financial system and covers the lack of research studies with the aim to investigate risk spill-over in the financial system (as one dimension of systemic risk).

2 Systemic Risk Measures – Theoretical Framework

There are many theoretical and empirical studies on contagion effect in the financial system. They are classified by Acharya et al. (2010), Hansen (2013) and Benoit et al. (2013). This section presents an analysis of measures with the focus on contagion.

Examples of measures of systemic risk focused on risk spill-over are given below. The following measures are used in the literature after the global financial crisis, i.e. after 2008:

1. Distress insurance premium (DIPI and DIPII; Huang et al., 2009, 2010, 2011).
2. Joint Probability of Default (JPoD), Banking Stability Index (BSI), Distress Dependence Matrix (DDM), Probability of Cascade Effects (PCE; Segoviano and Goodhart, 2009).
3. Spill-over indices (ReturnSI, VolatilitySI; Diebold and Yilmaz, 2009).
4. CoVaR (conditional VaR; Adrian and Brunnermeier, 2009, 2011, 2016).
5. Directed and undirected networks of international banking system linkages (Fender and McGuire, 2010).
6. Measures of contagion potential – Principal Component Analysis, Regime-Switching Models, Granger Causality Tests, Network Diagrams (Billio et al., 2010, 2012).
7. GDP at Risk (De Nicolo and Lucchetta, 2011).

8. Participation approach (PA), contribution approach (CA) and bottom-up approach (BA) measures (Drehmann and Tarashev, 2011).
9. Default intensity Model (DIM; Giesecke and Kim, 2011).
10. Composite Indicator of Systemic Stress (CISS; Hollo et al., 2012) (Hollo et al., 2012).
11. Systemic Contingent Claims Analysis (SCCA; Jobst and Gray, 2013).
12. Total and pairwise connectedness (Diebold and Yilmaz, 2014).

Among the extensive number of measures listed above, two tools to identify risk spill-over were selected: The Delta CoVaR measure and the principal component analysis.

Given the complexity of the financial system in a country, a single measure of contagion is not sufficient. The selection of these two measures is a result of combining delta CoVaR (well established in the systemic risk literature) with a measure less known in the principal components approach.

The delta CoVaR is a quantile-based risk measure, derived from the VaR concept. This measure is successfully exploited to measure systemic risk not only in the aspect of the contagion effect, but also in general terms of systemic risk. This measure allows to study spill-over effects across a whole financial system. The principal component captures commonality across returns within an institution. This approach can identify periods of market dislocation and distress, and can empirically detect increasing commonality among asset returns of a financial institution. The main purpose of these measures is to encompass the kind of systemic events in the financial system and their potential complementarity.

2.1 Conditional Value at Risk

CoVaR stands for conditional Value at Risk and is a systemic risk measure proposed by Adrian and Brunnermeier (2009, 2011). $CoVaR_q^{j|i}$ is formally defined as the *VaR* of the system (or institution) j conditional on institution i (bank) when this institution has reached its VaR_q^i at extreme quantile q (Adrian and Brunnermeier, 2009, 2011). The Delta CoVaR used in the empirical study is equal to

$$\Delta CoVaR_{q,t}^{j|i} = \hat{\beta}_q^{j|i} \left(VaR_{q,t}^{i} - VaR_{0.5,t}^{i} \right), \tag{1}$$

where β is a parameter which should be estimated. The most common approaches for beta estimation are, according to Adrian and Brunnermeier (2011), quantile regression, multivariate GARCH, copula functions, extreme value theory, and bootstrap. In this paper the quantile regression approach was utilized, the methodology developed by Koenker and Basset (1978) and extended by Koenker (2005).

2.2 Principal Component Analysis (PCA)

Increased commonality among the rates of return of companies can be identified by using the well-known principal components analysis (see e.g. Jolliffe, 2002; Kritzman et al., 2010). When the system is extensively interconnected, a small number of the first principal components may provide an explanation for the most of the risk in the financial system. In this paper the attention of the authors was brought towards 1, 3 and 5 first eigenvalues. This subset captures a larger part of the total volatility when the majority of rates of return tend to move together. Therefore, time periods in which the first principal component explains large percentage of the total volatility in the financial system are interpreted as periods when interconnectedness between financial institutions is high which was observed in periods of crisis (Billio et al., 2012, p. 543).

By examining the time variation, it is possible to detect increasing correlation among institutions, i.e., increased linkages and integration as well as similarities in risk exposures which can contribute to systemic risk. Risk associated with the first n components can be calculated as

$$\omega_n \equiv \sum_{k=1}^{n} \lambda_k, \tag{2}$$

where λ_k are eigenvalues.

3 Empirical Study on Risk Spill-Over in the Polish Financial System

In order to analyze systemic risk, the authors examined companies which operate in the financial industry and are listed on the Warsaw Stock Exchange. These are companies such as banks, investments and financial advisory firms together with debt collection companies. The span of analysis ranges from November 22nd 2004 until November 19th 2018. Since a sufficient set of data was comprised, the beginning for the analysis was established four years before the world financial crisis had begun. Therefore, a compromise between the number of companies listed and the length of the analysis period was reached. In consequence, eighteen companies were chosen. Weekly logarithmic rates of return for that period were calculated (731 observations). The data set (from Stooq.pl) was cleared from outliers. The financial system was approximated by the index WIG for banking industry (WIG_banks) and by a self-constructed index of the Polish financial system which included analyzed companies (selected from financial industry) weighted by their capitalization.

The financial institutions were analyzed from November 22nd 2004 until November 19th 2018. The year 2004 was appointed as the starting point for the analysis due to the fact that, in order to scrutinize the period of crisis, the delta CoVar estimation required an investigation long time before the crisis emerged. Soon after, the debt crisis in Europe took place and "the European crisis" (i.e. "Brexit") was initiated, therefore, it was crucial to extend the period of analysis until the end of 2018. In the empirical study three different periods were analyzed:

- November 22nd 2004–August 25th 2008 (197 observations) – before the global financial crisis,
- September 1st 2008–December 27th 2010 (122 observations) – the global financial crisis period,
- January 3rd 20011–November 19th 2018 (411 observations) – after the global financial crisis.

Delta CoVaR was estimated by adopting the methodology of Adrian and Brunnermeier (2011) with the important modification of using market data (prices of listed companies) instead of the companies financial data.

3.1 Descriptive Statistics Results

In the Tables 1–3 results of calculations of descriptive statistics and the autocorrelation function at lag 1 (ACF1) were presented. Analyzed companies were classified into such sections as banks, investment firms and "other" group (the results of median were included in Tables 1–3). In addition, results for WIG (broad market index) and WIG for the banking industry were included.

Table 1: November 22nd 2004–August 25th 2008 (197 observations).

	Banks	**Investment Companies**	**Other**	**WIG**	**WIG_banks**
mean	0.0032	0.0019	0.005	0.0024	0.0035
std	0.0467	0.1025	0.0976	0.0313	0.0367
min	−0.1434	−0.3065	−0.3201	−0.0985	−0.1189
max	0.1413	0.374	0.4705	0.0706	0.0997
median	0.0026	−0.0027	−0.0057	0.0066	0.0065
skew	−0.0653	0.6101	0.9238	−0.6847	−0.3045
kurt	4.7694	6.5448	7.5328	3.5689	3.2057
ACF(1)	−0.0226	0.0675	−0.0705	0.0396	−0.0377

Table 2: September 1st 2008–December 27th 2010 (122 observations).

	Banks	**Investment Companies**	**Other**	**WIG**	**WIG_banks**
mean	**0.0007**	**−0.0024**	**−0.0126**	**0.0012**	**0.0009**
std	**0.0618**	0.0721	**0.1118**	**0.0379**	**0.0578**
min	−0.1589	−0.2175	−0.3201	−0.0985	−0.1399
max	0.15	0.308	0.3347	0.0925	0.1469
median	**0.0016**	**−0.0053**	**−0.0103**	**0.0044**	**0.0009**
skew	−0.0684	0.7234	0.0073	**−0.236**	**−0.0878**
kurt	3.7587	**8.8772**	**7.7214**	3.5644	**3.8453**
ACF(1)	**0.0422**	−0.0652	−0.0787	**0.0634**	**0.037**

Table 3: January 3rd 2011–November 19th 2018 (411 observations).

	Banks	**Investment Companies**	**Other**	**WIG**	**WIG_banks**
mean	−0.0011	−0.0026	**−0.0018**	0.0005	0.0002
std	**0.0404**	**0.0682**	**0.0797**	**0.0209**	**0.0278**
min	−0.1502	−0.3071	−0.3126	−0.0985	−0.1223
max	0.138	0.3019	0.383	0.0524	0.0928
median	−0.0011	**−0.0012**	**−0.0009**	0.0003	−0.0012
skew	0.0503	−0.0787	**0.3596**	−0.4985	−0.0015
kurt	4.5768	**8.6184**	8.1209	4.285	4.0771
ACF(1)	−0.0607	−0.0684	−0.1295	−0.03	−0.0209

In the period of crisis lower rates of return, higher standard deviation, higher negative skewness, higher kurtosis and positive first-order autocorrelation (Billio et al., 2012) were expected. The values which met these expectations were printed in bold in Tables 2 and 3. It was detected by the authors that not all of these findings were present in the Polish market:

- Means of rates of return are lower – it is true for the “other” group of companies (they are lower for all groups of companies and indices but only in comparison to the “before the crisis period”).
- Medians of rates of return are lower – it is true for investment firms and “other” group of companies (they are lower for all groups of companies and indices but only comparing to the “before the crisis period”).
- Standard deviations are higher – it is almost true (it is smaller for investment companies comparing to the “before the crisis period”).
- Higher negative skewness – negative skewness is observed for banks and indices, but it is true only for WIG (it is higher for WIG_banks comparing to the “before the crisis period”).
- Higher kurtosis – it is true for investment firms (it is higher for “other” companies and WIG_banks comparing to the “before the crisis period”).
- Positive first-order autocorrelation – it is true for banks and indices.

These findings could be explained by a small number of analyzed companies (18) and relatively week influence of the global financial crisis on the Polish financial system.

3.2 Systemic Risk Analysis Results

Figure 1 shows that the first principal component (PCA(1)) varies dynamically over time, capturing from 18 % to 70 % of the variation of return rates. One may notice a significant increase during the global financial crisis. The PCA(1) eigenvalue started to rise slowly and peaked at 70 % in 2008, whereas in the middle of 2010 it declined substantially to 18 % and grew again in 2011 (when the debt crisis in Europe took place). Afterwards fluctuations took place and, finally, at the end of 2016 a new increase was observed. The PCA(1) explains around 70 % of the return variation over the global financial crisis of 20082010.

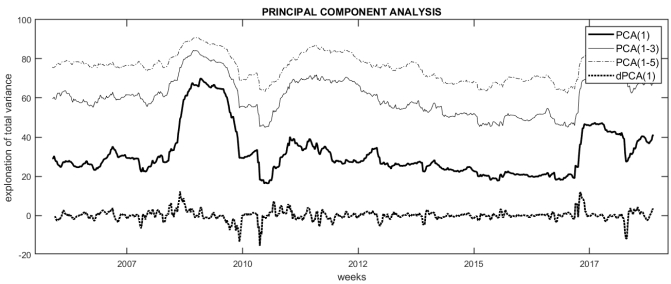

Figure 1: PCA.

As shown in Figure 1, the growing value of principal components supported by the growing coefficient dPCA(1) (first differences of PCA(1)) took place three times in the analyzed period: At the end of 2008 and later, in 2010 and again at the end of 2016 and later. It could be interpreted as the growth of systemic risk in these periods. To verify that growth of systemic risk, the authors calculated simple volatility measures (for indices) presented in Figure 2 and correlation coefficients (average) presented in Figure 3. Higher volatility of rates of returns and higher correlations between companies mean higher risk, also higher risk of risk spill-over. Looking at the GARCH result (Figure 2), the authors showed growing volatility in the periods indicated by PCA, which could support growth of systemic risk and risk spill-over there. Unfortunately, the authors could not confirm greater correlations between companies in the periods indicated by PCA (Figure 3). Such a correlation is observed during the global financial crisis 2008, and later during the debt crisis in Europe 2011.

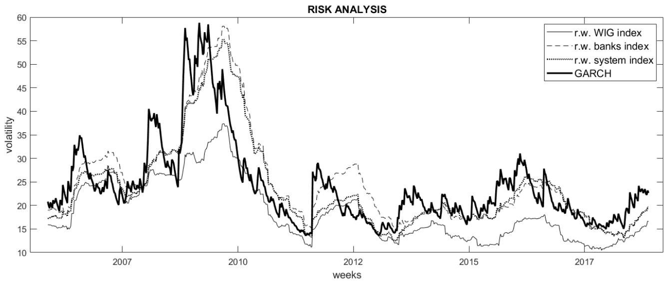

Figure 2: Volatility.

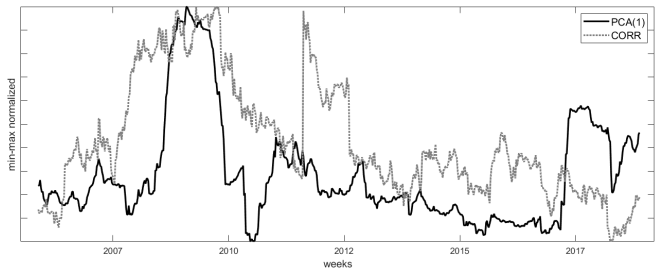

Figure 3: Correlation.

The analysis of companies from the financial industry was also conducted separately. Delta conditional Value at Risk was calculated and compared with PCA and volatility results for eighteen companies. A growing delta CoVaR measure indicates the growth of systemic risk. Regrettably, the authors did not find any patterns in delta CoVaR behavior for the analyzed companies (e.g. growth of delta CoVaR was not shown by systemic events). Some examples of these companies are presented in Figures 4–7. Looking at Figures 4–5, delta CoVaR supports two periods indicated by PCA, namely 2008, and 2016–2017.

However, there are examples of companies which did not correspond to those periods indicated by PCA, except for the global financial crisis period. While scrutinizing Figures 6–7, it is possible to find different periods of growing delta CoVaR in comparison to PCA.

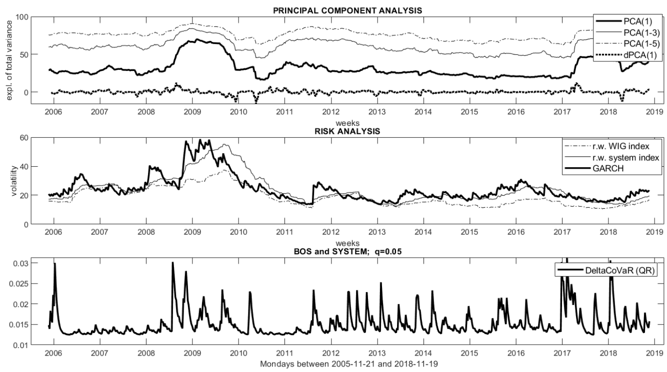

Figure 4: Bank Ochrony rodowiska SA (bank).

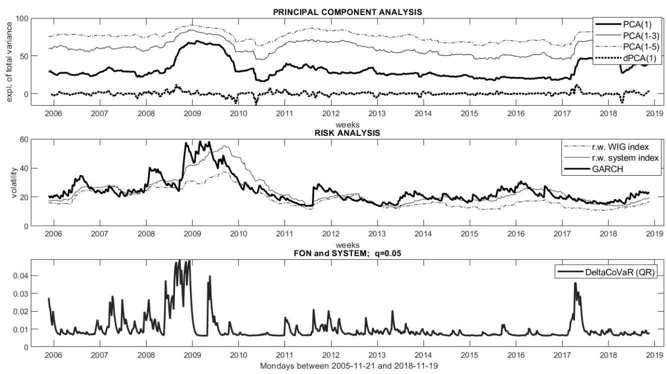

Figure 5: FON SA (financial intermediary, classified as “other”).

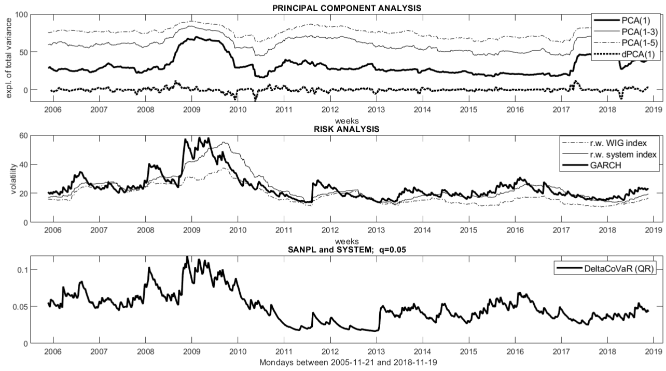

Figure 6: Santander Bank Polska SA (bank).

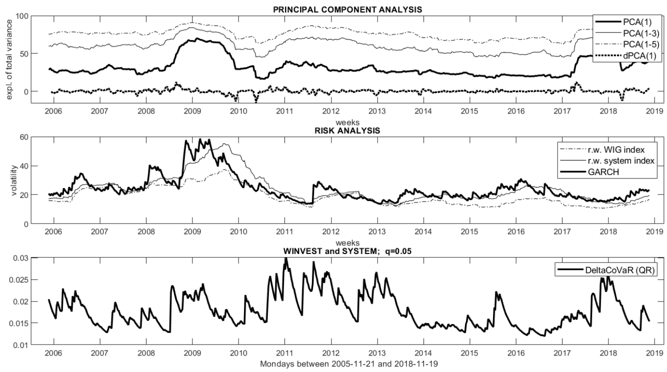

Figure 7: W Investment SA (financial services, classified as “other”).

Figure 8: SRISK (source: `www.vlab.stern.nyu.edu`).

To summarize the results obtained by all indicators directly (delta CoVaR) and indirectly (PCA, volatility, correlation), Table 4 on measured systemic risk was prepared. It is noticeable that measures such as PCA and delta CoVaR (also other considered measures) indicate only one period of high systemic risk for the Polish financial system, that is the global financial crisis. However, the results of PCA in comparison to SRISK results (an other measure of systemic risk proposed by Acharya et al. (2012) and extended by Brownlees and Engle (2016)) are more promising. Though, this result has to be confirmed in further research. This study put the emphasis on delta CoVaR and PCA as the approaches to identify risk spill-over (one dimension of systemic risk). SRISK is based on the concept of the Marginal Expected Shortfall (MES), a fragility-type of measure, and it depends heavily on the financial institution leverage effect. SRISK results for the financial system in Poland were collected from the V-Lab website (`www.vlab.stern.nyu.edu`).

Table 4: Summary of results.

Year/Period	**PCA**	**Delta CoVaR**	**Correlation**	**SRISK**	**Volatility**
2008–2009	+	+	+	+	+
2010	+			+	
2012			+	+	
2016–2017	+			+	

4 Conclusion

The authors stated that not all findings of the research conducted by Billio et al. (2012) were present in the Polish market. In the global financial crisis (2008–2010) lower rates of return, higher volatility and higher kurtosis were observed. Whereas, after the crisis (2011–2018), higher volatility and negative first-order autocorrelation were found. Two hypotheses were verified. The first demonstrated and proved that delta CoVaR and PCA were the proper tools to identify risk spill-over in the Polish financial system. Comparing to other measures of systemic risk, both of them indicated correctly the global financial crisis. Other measures of systemic risk (from the market frictions and fragility of the financial system dimensions) indicated only the financial crisis 2008–2010.

The latter, however, was verified as negative. Delta CoVaR and PCA as tools of identification of risk of spill-over provided different conclusions because

- PCA is a tool to identify risk spill-over for the financial system,
- The Delta CoVaR measure is an individual systemic risk measure (for an individual company).

The phenomenon of risk spill-over has many dimensions. Therefore, the presented tools of systemic risk measurement shall be treated as complementary among those dimensions.

These results could serve as a generalized analysis for other cases, but deeper investigation among measures and a thorough analysis across advanced economies are necessary. The results obtained for the financial system in Poland which remains the largest economy in Central and Eastern Europe are very promising when considering contagion as a dimension of systemic risk, particularly due to the fact that Poland managed to prevent the recession during the global downturn of 2009.

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