EARLY WARNING SYSTEM FOR THE EUROPEAN INSURANCE SECTOR

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Abstract- This study proposes an Early Warning System model composed of macro-financial and company-specific indicators that could help to anticipate a potential market distress in the European insurance sector. A distress is defined as periods in which insurance companies' equity prices crash and CDS spreads spike simultaneously. The model is estimated using a sample of 43 insurance companies that are listed. Based on a panel binomial logit specification, empirical evidence shows that economic overheating that could be manifested by high economic growth and inflation as well as high interest rates have negative impact on insurance sector stability. At the company level, increasing operating expenses increase the likelihood of distress occurrence.

Keywords- early warning system, insurance sector, financial distress JEL Classification: G01, G12, G22, E44

I. INTRODUCTION

The devastating impact of the financial crisis of 2008-09 has urgently posed the question to raise awareness of an early detection of potential factors which can lead to a crisis. In this respect, policymakers interest has increasingly focused on a crisis prevention and prediction of risks of systemic nature. Although there is not a universally recognized definition of systemic risk, it is possible to refer to it as the risk that some trigger events cause such a widespread financial instability that it impairs the functioning of the financial system to the extent that economic growth and welfare suffer materially (ECB, 2009). A recursive problem with past approaches by financial regulators to the crises has been to deal with each institution's risk in isolation. This implied that firms may have taken actions to prevent their own collapse, but not necessarily to avoid the collapse of the whole system (Acharya and Richardson, 2014). Within the recent academic literature, there is an elaborated view on the causes of systemic, banking and stock markets crises, which sheds light on potential mitigating regulatory interventions. The insurance industry, despite its relevance in the financial system, has been at the margin of research interest and, as a consequence, several aspects of its potential sources of systemic risk are still partially latent. The limited focus on measuring risk in the insurance industry derives from the traditional view of insurers being considered safer than other financial institutions.[1] Notwithstanding, the near-miss and government bailout of AIG has drastically changed this point of view. Indeed, the events of the recent financial crisis showed that turmoil and clients' runs can be extended even to non-banking institutions such as money market funds or insurance companies. Whatsoever the origins of distress, neither existing literature nor contemporary models pay much attention to identify and develop possible measures of systemic risk, designed to facilitate monitoring and regulation of insurers.

To fill this gap, this study proposes an Early Warning System (EWS) model examining the causes of market distress in the insurance sector. Section 2 elaborates on the available studies on EWS in literature. Section 3 provides a description of the applied methodology and the employed dataset. On this basis, section 5 presents the obtained empirical results. The last section concludes.

II. LITERATURE REVIEW

The global financial crisis increased the interest of researchers and policy makers alike in putting considerable effort into understanding and predicting systemic crises. Despite there is an elaborated view of Early Warning System models in the banking sector as well as in assessing risk and predicting systemic events in the aggregate economy supported by the extensive literature, not much research focuses on the insurance sector could be found.

Davis and Karim (2008) underline and push forward the need of practical use of EWS to predict banking crisis. In their seminal paper they assess the properties of a logit-model EWS compared to a signal-extraction method for banking crisis, using a comprehensive dataset of 105 countries for the period from 1979 to 2003. The outcome of the research leans towards the better performance of the logit model in predicting global crisis and the signal approach being

[1] Statement reported e.g. by Valckx et al. (2016) in the third chapter of the Global Financial Stability Report by the IMF (2016).

superior in predicting country-specific crisis. The main drivers to banking crises in their sample are terms of trade and growth.

Alessi and Detken (2011) contribute to the financial crisis literature testing the performance of real and financial variables as Early Warning indicators for costly aggregate asset price booms/bust cycles. In this respect, they use a combination of the price index of weighted real private property, commercial property and equity prices to identify asset price booms. Their results show that it is possible to find early warning indicators that perform reasonably well for individual countries and also for groups of countries. They found financial variables as the best predictors of price booms, in particular the global private credit gap.

Likewise, Lo Duca and Peltonen (2013) complete the build-up on the methodology through the assessment of systemic risk and prediction of systemic events. The novelty of their paper is the definition of systemic events rather than the methodology itself. They identify systemic events as "episodes of financial stress that has led to negative real economic consequences", using a composite index measuring the level of systemic events in the financial system of a country. In this respect, stand-alone measures of asset price misalignments and credit booms are typically useful indicators that anticipate systemic events

Notable exceptions for the insurance sector are Billio et al. (2012) and Chen et al. (2014) who attempt to establish econometric measures of systemic risk in the insurance sector.

III. DATA SAMPLE AND METHODOLOGICAL BACKGROUND

In order to understand the transmission channels through which risks materialize at the event of crisis in the insurance sector, it is necessary to lay down the methodology that allows tackling such a challenge. As data on insurers' default are not available, the concept of insurers' distress using available market data is employed. Furthermore, the list of potential variables that could serve as early warning indicators is provided. Finally, the modeling framework allowing to use those indicators to predict an insurer's distress is described.

3.1. Sample Description

Given that the study is based on market data only, the aim is to include as many listed companies as possible. There are 109 listed (re)insurers in Europe, but individual level statistics are available for less than half of them. Therefore, the sample has to be narrowed to 43 listed (re)insurance entities (7 solos and 36 groups), located across the European countries. More specifically, solo (re)insurers are from Denmark, Germany, Great Britain, Italy, and Switzerland. The final sample is decomposed into 7 property and casualty, 22 Multi-line, 10 Life & Health, and 4 reinsurance companies. The sample encompasses the top 30 European groups, 6 other groups, and 7 solo insurers. This corresponds to a market coverage of 75% based on total assets.[2] Hence, it is possible to consider that the sample is representative for the EU.[3]

Furthermore, the sample covers the years from 2004 to 2017.[4] The company data were complemented with macroeconomic/financial data. While European level data were used for the groups, country level data were utilized for solos. In all cases market data, as well as balance sheet indicators, have been extracted from the Bloomberg platform. The data warehouse of the European Central Bank and the database of Eurostat were used for macroeconomic indicators. Concerning Switzerland, observations are taken from the data stock of the Swiss National Bank. Since many balance sheet items are reported annually, yearly data rather than quarterly or monthly are employed.

3.2. The insurance sector distress

In absence of data on insurers' defaults, the main challenge in developing early warning systems is the definition of proxy for insurance sector distress. Market valuations of publicly traded companies are a reflection of their overall financial healthiness. Specifically, markets mirror investors' expectations of the ability of corporations to generate future profits. The proxy indicators capturing insurers' distress should reflect markets' uncertainties and imbalances. Hence, the crash in the company-specific market share price with a simultaneous spike in the company-specific issued Credit Default Swap (CDS) spread are employed in this paper to define insurers' distress. A sudden crash of the stock price might reflect emerging economic crisis as well as serious catastrophic events. Similarly, an increase in insurance CDS spreads corresponds to the higher likelihood of the insurer to default on its debt. The employed approach is based on seminal literature related to the measurement of systemic risk in the insurance sector. Chen et al. (2014) uses CDS spreads and intra-day stock prices as terms of reference to estimate the probability of default of insurers and the default correlations respectively. Furthermore, Billio et al. (2012) use monthly returns data of financial institutions (insurers included) as main indicator for the establishment of measures of systemic risk in financial and insurance sectors. Finally, Gottschalka

[2] Based on EIOPA Solvency II statistics.

[3] Most solos across Europe are not listed and, if they are, do not report their financial data in many cases.

[4] The sample was reduced to 2016 in a second stage, since some figures for 2017 of the sample countries were not available at the time of conducting this study.

and Walkerb (2011) show that CDS changes have predictive power over corporate defaults.

3.3. Definition of the dependent variable

In order to measure insurance distress, the market stress index (MSI) incorporates both the effects of CDS spikes and equity price crashes. The both components are calibrated in a way that they reflect annual changes (in this respect see e.g. Corsi, 2009).[5] The MSI is calculated as the arithmetic average of the CDS realized volatility and the realized share price volatility for each company i at time t.[6]

$$MSI_{i,t} = \frac{\sigma_{CDS_{it}} + \sigma_{Price_{it}}}{2}$$

After the computation, a percentile rank is assigned to each of the values of the MSI such that, every year, for each company, the indicator is ranked between 0 and 1. The crucial feature of the EWS framework is the identification of crisis events from the specific market stress measure, as it indicates crisis occurrence (or absence), that is used as a dependent variable for the purpose of the study. Therefore, it is necessary to set an appropriate threshold above which the company-specific MSI would capture crisis events. In this respect, the values of the index of the 43 companies are aggregated using weighted average, obtaining a new indicator capturing one average single value each year. This allows to establish common standards for crisis signaling. Furthermore, percentile values are assigned, so that the aggregate MSI ranks between 0 and 1. High values of the indicator represent periods of distress. The construction of the aggregate index is challenged by the trade-off between guaranteeing a certain extent of precision at the company level, at the expense of uniformity across the sample, and ensuring homogeneity across companies and time. The cross-section dimension of the panel dominates in this study; therefore, priority is given to homogeneity across companies because the objective is to calculate average distress in the sector as a whole.

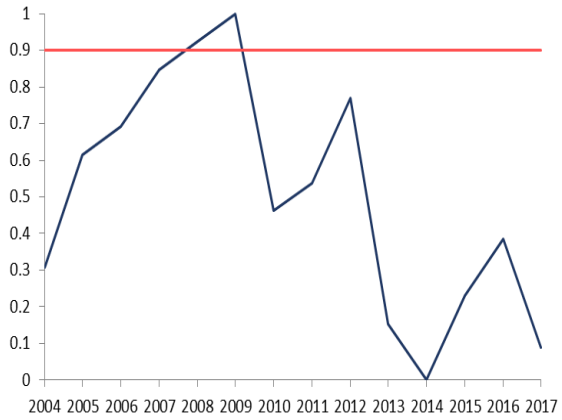
In order to make sure that the MSI behaves as a proper early warning indicator by signaling upcoming distress events, it is necessary to introduce a binary variable (D_{it}) that takes the value of 1 in the most unfavorable outcome and 0 otherwise. In this sense, when the individual MSI crosses the predefined threshold (m), the parameter takes the value of 1, signaling distress.

$$D_{it} = \begin{cases} 1 & \text{if } MSI_{it} \geq m \\ 0, & \text{otherwise} \end{cases}$$

Finally, the major concern is that the "post-crisis bias" could alter the final results. Indeed, it could be the case that the econometric results of models that try to explain or predict crises can at least in part, or even fully be explained by the behavior of the independent variables during and directly after a crisis (Bussiere and Fratzscher, 2006). Therefore, in a second stage, all consecutive periods of distress (e.g. years in which the MSI equals 1, but had already signaled distress the previous period) are dropped from the sample.

Figure 1 displays the aggregate MSI. The index is able to capture the great recession of 2008-09, the sovereign debt crisis of 2012, and in a minor way Brexit in 2016. The reliability of the indicator stands in the fact that it captures the three historical events that most negatively characterized the whole economy within the last 13 years. In this spirit, the threshold at the 90th percentile of the distribution (red line) captures periods of extreme crisis such as the Great Recession.[7] Following the methodology from Lo Duca and Peltonen (2013), the 90th percentile is the benchmark that reflects real consequences on average, observing GDP growth severely dropping below zero to -4.3%.

Figure 1: Aggregate Market Stress Indicator



3.4. Explanatory variable choice

The Early Warning Systems aim to predict events of stress using several forward-looking variables. While the relevance of macroeconomic variables has been vastly explored, the role of balance sheet items still lack some research. In order to contribute to close this

[5] Equity price and CDS spreads raw observations are trending daily measures.

[6] A more complex weight calibration reflecting the specific features of the relevant markets might vary over time therefore both components are given equal importance. For example, weight assignment in relatively tranquil years (e.g. 2004-05) would not be equal to that in more harmful periods (2008-09).

[7] The attempt to set the threshold at the 75th percentile did not yield satisfactory results. Setting only the threshold at the 75th percentile may be too vague since it captures all the distress, but, at the same time, may also be likely to issue false alarms. Raising the threshold allows to reduce the likelihood of type I errors, at the expense of increasing the frequency of ignoring actual episodes of distress.

gap, a pre-selection of plausible variables will include both macroeconomic and company-level indicators. It is expected that at the macroeconomic level, episodes of distress are anticipated by economic overheating (high interest rate, high inflation and unsustainable GDP growth). At the company level, imbalances are characterized by drops in profitability and increases in costs of managing claims.

Table 1: List of indicators considered

Indicator	First Difference	Percentage Change	Expected Sign
Real GDP Growth		x	+
Long-term Government Bond Yield	x		+
Inflation		x	+
Decomposition of Real GDP		x	+
Cash Flow to Net Income	x		-
Net Written Premia		x	-
Operating Expenses		x	+
Underwriting Costs		x	+
Return On Assets	x		-
Return on Equity	x		-
Price to book value	x		-
Price-Earnings Ratio	x		-

To avoid any kind of endogeneity bias, as well as to fulfill the role of "early" warning indicators, all explanatory variables have been lagged by one year. In this way the occurrence of reverse causality is avoided, as it could be the case that the crisis itself may hit simultaneously some explanatory variables values. Furthermore, all potential indicators are expressed in growth rates or first differences in order to guarantee their stationarity.

3.5 The model

In order to explain risk of potential distress in the insurance sector, the study will rely on a binomial logit approach. This allows identifying those indicators that positively or negatively affect the likelihood of distress. The simple logit panel regression can be expressed as follows:

$$\text{Prob}(D_{it} = 1) = \frac{e^{(X_{t-1}\beta'_{i,t-1} + Z_{i,t}\gamma'_{i,t-1})}}{1 + e^{(X_{t-1}\beta'_{i,t-1} + Z_{i,t}\gamma'_{i,t-1})}}$$

where $\text{Prob}(D_{i,t} = 1)$ is the probability that company i at time t is in state of distress. The vector $X_{i,t}$ contains the set of different independent macroeconomic variables presented in the previous paragraph. On the other hand, the vector $Z_{i,t}$ corresponds to the company-specific indicators. The underlying goal is to find a set of indicators, which predicts crises well in advance, such that potential policy maker actions would be effective.

IV. EMPIRICAL RESULTS

To identify a set of predictive EWS indicators, the binomial logit model at the predefined threshold is ran and the sign and the significance of the coefficients are checked at the first step. In a second stage, the classical methodology requires the assessment of the in-sample performance of the model, which can be classified via the area under the ROC curve. Given the nature of the logit model, the coefficients take the form of log-odds ratios. In this respect, estimates should be interpreted in terms of how the likelihood of an event of distress evolves as the explanatory variables change by a unit. Quantitatively, for a one unit increase in the explanatory variables, it is expected an increase in the log-odds ratio of the dependent variable equal to the coefficient reported. The sign in front of the coefficient indicates the positive or negative likelihood of the occurrence of an unfavorable event.
Table 2 shows the results of the model including only macroeconomic variables. Results suggest that positive GDP growth, high level of long term interest rate, and elevated inflation increase the likelihood of a crisis event in the insurance sector in one-year horizon. The positive sign in front of the coefficients is in line with the theory. When splitting down GDP into its components, extreme crisis episodes are more likely to occur when government expenditure and disposable income are high.

Table 2: EWS model with macroeconomic variables only

(1)	(2)	(3)	(4)
	Distress1	Distress1	Distress1	Distress1
GDP	0.838***	0.334*		
	(0.000)	(0.071)		
Inflation	1.329***	0.641**	1.051***	0.634**
	(0.000)	(0.027)	(0.004)	(0.025)
Long term IR		1.782***	2.128***	2.229***
		(0.000)	(0.000)	(0.000)
Consumption			1.490***	
			(0.006)	
Investment			-0.0425	0.0939
			(0.669)	(0.262)
Government expenditure			0.176	0.719**
			(0.645)	(0.029)
Export			0.194	0.146
			(0.292)	(0.384)
Import			-0.336*	-0.219*
			(0.094)	(0.097)
Household disposable income				0.399*
				(0.074)
Number of observations	490	490	490	490
R^2	0.242	0.301	0.410	0.383

p-values in parentheses
*** p<0.1, ** p<0.05, *** p<0.01**

The combination of macroeconomic and company level data, shows that GDP growth, interest rate level and inflation maintain their sign and statistical significance (Table 3). Although the coefficient is quite small in terms of weight (a one unit increase in operating expenses increases the log-odds of distress by 0.00134), extensive operating expenses costs increase probability of insurer's distress. A drop in return on assets, which can be interpreted as a proxy for profitability, tend to increase the probability of distress. This highlights the initial insurers internal difficulties that are accompanied by macroeconomic imbalances at the eve of the crisis. When combining macroeconomic and balance sheet data, GDP growth loses significance.

Table 3: EWS model with macroeconomic variables and balance sheet indicators

(1)	(2)	(3)	(4)	(5)	(6)
	Distress	Distress	Distress	Distress	Distress	Distress
GDP	0.334*		0.259		0.207	0.0105
	(0.071)		(0.159)		(0.275)	(0.957)
Inflation	0.641** (0.027)		0.690** (0.017)		0.898*** (0.005)	1.105*** (0.001)
Long term IR	1.782*** (0.000)		1.826*** (0.000)		1.667*** (0.002)	1.903*** (0.001)
Price-to-earning ratio		-0.00246	0.00191			-0.00418
		(0.812)	(0.851)			(0.843)
Price-to-book value		0.430**	0.278			0.527*
		(0.015)	(0.127)			(0.058)
ROA		-0.206** (0.049)				-0.351** (0.023)
ROE		0.0399* (0.084)				0.0859** (0.037)
CF to net income				-0.00337	-0.00889	-0.000996
				(0.805)	(0.661)	(0.965)
Net premiums				0.0140	0.0173	0.0179
				(0.187)	(0.200)	(0.216)
Operating expenses				0.00147*	0.00145	0.00125*
				(0.050)	(0.102)	(0.071)
Underwriting costs				0.00338	0.00448	0.00440
				(0.358)	(0.253)	(0.276)
Number of observations	490	487	488	371	371	371
R^2	0.301	0.039	0.311	0.035	0.332	0.379

p-values in parentheses * p<0.1, ** p<0.05, *** p<0.01

V. MODEL PERFORMANCE EVALUATION

A valuable tool to assess the performance of a logit model is the Receiving Operator Characteristics (ROC) Curve, which disply the ratio of true distress signals (sensitivity) over false alarms (1-specificity).[8] The advantage of this method is that with multiple regressors it is possible to construct a curve that shows the sensitivity and specificity of the model for each and every cutoff point.[9]

In other words, it summarizes the predictive power of the indicators for all possible thresholds. For this reason, as post-estimation classification, the ROC curve is more informative than the confusion matrix. Therefore, to test goodness of fit or in other words the reliability of the model, the analysis relies on the magnitude of the area under the ROC curve (AUROC) generated by the models presented above. The AUROC ranges between 0 and 1. The closer the AUROC produced by the Early Warning System gets to 1, the better the predictive accuracy. Hence, for values greater than 0.5 the EWS model can be considered to hold some predictive power.[10]

Table 4 shows the AUROC scores for the models employed in this study. Even when controlling for company specific factors, the performance of the model does not deteriorate. The rate of correctly signaled crisis is kept quite high, with the magnitude of AUROC scorning between the range of 0.80-0.85.

Table 4: Model Performance Comparison[11]

Model	90th Percentile
AUROC GDP	0.8149
AUROC GDP - Decomposed	0.8845
AUROC Companies' Variables	0.8342

[8] Sensitivity measures the ability of the model to correctly classify episodes of distress. Specificity measures the correct classification of tranquil periods.

[9] Cut-off points can be set up according to the policymaker preferences. The higher the cut-off point, the higher the policymaker preference towards detecting distress periods regardless of false alarms.

[10] AUROC = 1 corresponds to perfect classification; AUROC = 0 corresponds to random guess.

[11] AUROC GDP shows performance score for the model results of Column (2) in Table 2. AUROC GDP – Decomposed shows performance score for the model results of Column (4) in Table 2. AUROC Companies' Variables shows performance score for the model results of Column (6) in Table 3.

CONCLUSION

This article contributes to the existing literature by developing an early warning system (EWS) being able to anticipate a period of financial distress in the European insurance sector. The employed empirical analysis is based on a set of 36 insurance groups and 7 insurance solos with yearly data covering years 2004 - 2017. The study employs the concept of market distress applied for the insurance sector. In this respect, the Market Stress Index (MSI) is calculated as the arithmetic average of the CDS realized volatility and the realized share price volatility for each insurance company at every point in time. In the next step the value of the index is transferred into quantiles and subsequently transformed into a binomial variable using a threshold that is able to capture historical distress in the sector for the aggregated MSI. Finally, this variable is employed to develop an EWS model for the insurance sector.

The obtained results suggest that interest rate as well as other macroeconomic related risks are the main sources of instability in the sector. In particular, the empirical evidence reveals that market imbalances are anticipated by economic overheating, characterized by high interest rates, positive unsustainable growth and high inflation. When further determinants of economic growth are considered, investment growth, terms of trade, and household disposable income could explain a potential distress in the insurance sector. Moreover, including company-specific variables could further help to anticipate distress in the sector. The conducted analysis reveals that extensive operating expenses costs and a drop in return on assets could also anticipate insurer's distress.

Being aware of the sources of risk allows policymakers to take appropriate policy responses. Some risks can be mitigated through supervision guidance both at the national and European level ensuring level playing field for insurance undertakings across the continent. Nevertheless, signals obtained by the provided toolkit should be interpreted carefully and assessed only in the context of all supervisory information and tools available.

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