

## Early Warning System for the European Insurance Sector<sup>1</sup>

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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 36 insurance companies that are listed. Based on a fixed-effects panel binomial logit specification, empirical evidence shows that economic overheating that could be manifested by high economic growth, inflation and interest rates have negative impact on insurance sector stability. At the company level, a drop in return on assets and price-to-book value or raising operating expenses increase the likelihood of distress occurrence.*

**Keywords:** early warning system, insurance sector, financial distress

**JEL Classification:** G01, G12, G22, E44

**DOI:** <https://doi.org/10.31577/ekoncas.2022.01.01>

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### Introduction

The devastating impact of the financial and subsequent economic crisis in 2008 – 2009 has urgently posed the need to raise awareness of an early detection of potential factors that could lead to a crisis. In this respect, policymakers' interest

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<sup>1</sup> Financial support from the Czech Science Foundation (Project No. GA 20-00178S) is gratefully acknowledged by Petr Jakubik. The views expressed in this paper are exclusively those of the authors and do not necessarily reflect those of the institutions with which the authors are affiliated.

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 was to deal with each institution's risk in isolation. This implied that firms might 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 growing importance in the financial system, has been originally at the margin of research interest. The limited focus on measuring risk in insurance sectors derives from the traditional view of insurers being considered safer than other financial institutions.<sup>2</sup> It was further supported by the fact that the financial and subsequent economic crisis in 2008 – 2009 affected insurance sector only marginally (e.g. Harrington, 2009). Financial problems of AIG and few mainly U.S. based insurers were rather exceptional cases. Moreover, the main reason of their problems was not an insurance core business. As a consequence, aspects of insurers' potential sources of systemic risk have been out of central attention for some time. However, as a result of the crisis, the European System of Financial Supervision (ESFS) was introduced in 2010 and became operational on 1 January 2011. The European Insurance and Occupational Pensions Authority (EIOPA) was established as a part of ESFS. Subsequently, Solvency II regime was introduced in 2016 to harmonize and strengthen the EU insurance regulation. This development has further supported a discussion on identifying and analysing the sources of systemic risk also in the insurance sector (EIOPA, 2017a). Despite only a few limited cases of the near miss, financial rating downgrades and government bailout of insurers have been observed showing that clients' runs can be extended even to non-banking institutions such as insurance companies. Moreover, we have experienced many new challenges since the financial and economic crisis in 2008 – 2009. Some of them such as Brexit or the pandemic crisis might evoke important systemic risk with a potential to significantly affect insurance sectors.

In this respect, this paper constructs an Early Warning System (EWS) model examining the causes of market distress in the insurance sector. Towards this

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<sup>2</sup> Statement reported e.g. by Valcckx et al. (2016) in the third chapter of the Global Financial Stability Report by the IMF.

aim we leverage on the work done by IAIS (2019) and EIOPA (2017a; 2018a; 2018b and 2019) that elaborates on the main sources of systemic risk for insurance companies and potential tools and policies for their mitigation. Our study contributes to the literature by assessing indicators that could predict systemic distress in the European insurance sector. The proposed EWS model could complement the existing financial stability framework to monitor systemic risk. The paper is structured as follow. Section 1 elaborates on the available studies on EWS and systemic risk in the existing literature. Section 2 provides a description of the applied methodology and the employed dataset. On this basis, section 3 presents the obtained empirical results. The performance of the estimated model is provided in section 4 and the last section concludes.

## **1. Literature Review**

The first steps towards revealing the causes of crises were done by Kaminsky and Reinhart (1999) by assessing vulnerabilities of the economy at the origin of crises. They find that banking and currency crises are closely linked right after episodes of financial liberalization, with currency collapses anticipating banking crisis. The main feature of their approach is the quantification of systemic risk through an index capturing market turbulences via the weighted average of changes in exchange rate and reserves. Similar methodology has been carried out by Borio and Drehmann (2009) who employ credits, asset prices and investments as predictors of turmoil in the financial system. In particular, they try to assess whether a strong increase in one of the mentioned components could provide an early signal of an upcoming financial crisis. They use information available to policymakers at the time of assessment to determine a potential distress. In this respect, they use a combination of several indicators. An important consequence of this approach is the establishment of threshold values defining the existence of slowdown in the system. In the end, they show that widespread financial distress usually stems from the release of financial imbalances that build up hiding behind benign economic conditions.

Many studies focus particularly on banking or currency crises applying a binomial logit approach. In a forerunner paper in this area, Martin (1977) rises the discussion on how to measure the soundness of commercial banking systems. He constructs an early warning model expressing the probability of future failure as a function of variables obtained from the balance sheets and income statements. 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 crises and the signal approach being superior in predicting country-specific crises. The main drivers to banking crises in their sample are terms of trade and economic growth. Jorda et al. (2011) use a long-run annual dataset for 14 countries to develop a probabilistic model of the occurrence of financial crisis event as a function of lagged macroeconomic fundamentals. Their findings show that credit growth emerges as the single best predictor of financial instability. Comelli (2014) provides a comparison between logit and probit early warning systems for currency crisis in emerging market economies. The employed logit EWS is able to classify correctly between 42% and 66% of the periods of crisis, defined as the exchange rate pressure index being two standard deviations above its mean.

Alessi and Detken (2011) contribute to the financial crisis literature by 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 weighted combination of the price indices of 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 as well as 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 of 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 country. In this respect, stand-alone measures of asset price misalignments and credit booms are typically useful indicators that anticipate systemic events. Also, Anundsen et al. (2016) stress the importance of house prices and credit in affecting the likelihood of financial crisis.

Compared to studies on banking sectors' failures, the literature focusing on insurance sector is more limited. Billio et al. (2012) use principal-components analysis and Granger-causality networks to measure interconnectedness of hedge funds, banks, brokers/dealers and insurers. They suggest that all four sectors become highly interrelated that likely increasing systemic risk. Their framework seems to have some predictive power to identify and quantify a potential financial crisis. Similarly, Chen et al. (2014) examine the interconnectedness between banks and insurers using Granger causality tests. In line with (Billio et al., 2012), the study suggests that banks create significant systemic risk for insurers but not

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vice versa. Moreover, with the introduction of Solvency II framework and establishment of ESFS, the systemic risk in relation to the European insurance market become more in the centre of attention. In this respect, EIOPA highlights that the financial crisis has shown the need to further consider the way in which systemic risk is created and/or amplified, as well as the need to have proper policies in place to address those risks. It was also recognized that most of the discussions on macroprudential policy have focused on the banking sector due to its prominent role in the financial crisis (2017a). Given the relevance of the topic, EIOPA initiated the publication of a series of papers on systemic risk and macroprudential policy in insurance with the aim of contributing to the debate and ensuring that any extension of this debate to the insurance sector reflects the specific nature of the insurance business (EIOPA, 2017a; 2018a; 2018b). Moreover, the holistic framework for systemic risk in insurance was outlined at international level by IAIS (2019). This also provides base for further research in this area.

Getmansky et al. (2020) suggest an empirical measure to assess to which extent insurers holding similar assets as a result of their shared business model may negatively impact prices when jointly liquidate those assets. They suggest that the proposed portfolio similarity measure can be used by regulators to predict the common selling of any institution that reports security or asset class level holdings. Moreover, it could serve an ex-ante measure of systemic risk stemming from the collective divestment decisions of financial institutions. Finally, Eling and Jia (2018) focus directly on insurers' distress predictions employing eight-year sample (2006 – 2013) of 2,060 Europe-based insurers. They apply a standard logit regression, rare event logistic regression, hazard model of time to failure, and supporting vector machine approaches to the business failure prediction. The failure events include ceased operations, in liquidation or liquidated, in runoff, portfolio transfer, inactive, and insolvent. A financially distressed observation is defined for those when failure event occurs to the firm in the year or in the next two years. Their results suggest that both company specific and macroeconomic factors could explain distress of insurers.

Our paper contributes to the existing literature of Early Warning System models for insurers covering a longer time period compared to (Eling and Jia, 2018) containing several stress periods including the pandemic crisis in 2020.

## **2. 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 employ the methodology that allows tackling such a challenge. Due to limited availability of

data on insurers' default, the concept of insurers' distress is captured through available market data. Furthermore, the list of potential variables that could serve as early warning indicators is provided. Finally, the modelling framework allowing to use those indicators to predict an insurer's distress is described.

## 2.1. Sample Description

Given that the study is based on market data only, the aim is to include as many listed companies as possible. There were 109 listed (re)insurers in Europe at the time of conducting the study, but individual level statistics were available for less than half of them.<sup>3</sup> Therefore, the sample has to be narrowed to 36 listed (re)insurance entities, 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 4 property and casualty, 20 multi-line, 8 life & health, and 4 reinsurance companies. The sample encompasses the top 26 European groups, 6 other groups, and 4 solo insurers. This corresponds to a market coverage around 75% based on total assets of the European Economic Area (EEA). Hence, it is possible to consider that the sample is representative for the EEA.<sup>4</sup>

Furthermore, the sample covers the period from 2004 to 2020. The company specific 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 and Refinitiv Eikon platforms. 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.

## 2.2. The Insurance Sector Distress

In absence of data on insurers' defaults, the main challenge in developing early warning systems is the definition of a 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 representative indicators capturing insurers' distress should reflect markets' uncertainties and imbalances. Hence,

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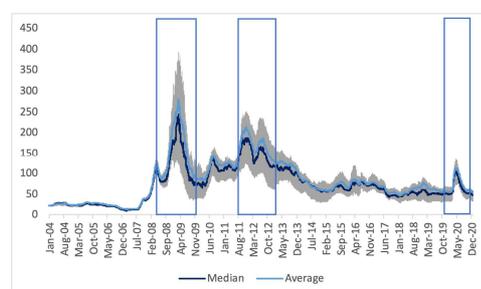
<sup>3</sup> Moreover, 4 companies were delisted by the time the statistics were updated and 3 companies ceased to provide data to commercial databases.

<sup>4</sup> Most solos across Europe are not listed and, if they are, do not report their financial data in many cases.

this paper employs the crash in the company-specific market share price with a simultaneous spike in the company-specific issued Credit Default Swap (CDS) spread to define insurers' distress. A sudden crash of insurance stock prices 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 evolution of CDS spreads and share prices over time reflect three historical periods of crisis (see Figure 1 and 2).

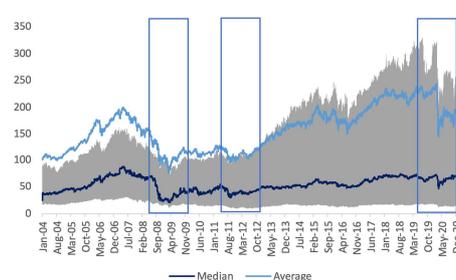
**Figure 1**  
**CDS Spread**



*Note:* Daily average (light blue line) and median (dark blue line) CDS spread of the 36 insurance companies in the sample from 01/01/2004 to 31/12/2020. Grey-shaded area represents the interquartile range.

*Source:* Bloomberg.

**Figure 2**  
**Share Price**



*Note:* Daily average (light blue line) and median (dark blue line) share price of the 36 insurance companies in the sample from 01/01/2004 to 31/12/2020. Grey-shaded area represents the interquartile range.

*Source:* Bloomberg.

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

### 2.3. Definition of the Dependent Variable

In order to measure insurance distress, the market stress index (MSI) combines both the effects of CDS spikes and equity price crashes. Both components are calibrated in a way that they reflect annual changes (in this respect see e.g. Corsi, 2009).<sup>5</sup> 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  $t$ .<sup>6</sup>

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

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 36 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 signalling. 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 signalling upcoming distress events, it is necessary to introduce a binary variable ( $D_{it}$ ) that takes the value of 1 in the most unfavourable outcome and 0 otherwise. In this sense, when the individual MSI crosses the predefined threshold ( $m$ ), the parameter takes the value of 1, signalling 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 behaviour 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 signalled distress the previous period) are dropped from the sample.

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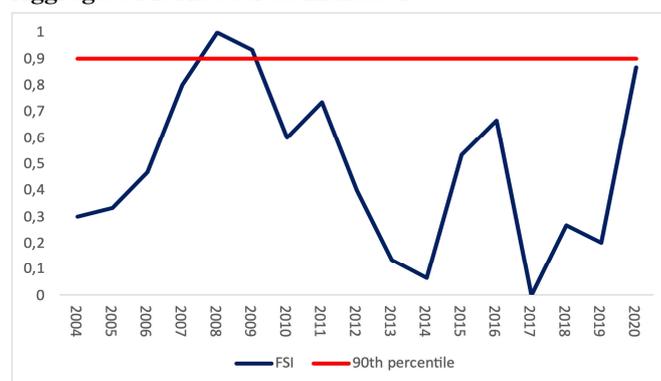
<sup>5</sup> Equity price and CDS spreads raw observations are trending daily measures.

<sup>6</sup> 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 – 2005) would not be equal to that in more harmful periods (2008 – 2009).

The aggregate MSI is able to capture the great recession of 2008 – 2009, the sovereign debt crisis of 2012, the financial turmoil around the Brexit announcement in 2016 and the financial market crash during the Covid-19 crisis (Figure 3). 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 17 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.<sup>7</sup> Following the methodology from Lo Duca and Peltonen (2013), the 90th percentile is used as the benchmark that reflects real consequences on average, observing GDP growth severely dropping below zero to  $-4.3\%$ .

Figure 3

#### Aggregate Market Stress Indicator



Source: Bloomberg and authors' calculations.

#### 2.4. 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 is more limited, e.g. (Eling and Jia, 2018). In order to contribute to the existing research literature, a pre-selection of plausible variables 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. The assumption

<sup>7</sup> The attempt to set the threshold at the 75<sup>th</sup> percentile did not yield satisfactory results. Setting only the threshold at the 75<sup>th</sup> 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.

of economic overheating is less true for sudden crisis periods driven by peripheral events such as the Covid-19 pandemic. In this respect, the pandemic came after a relatively calm period in financial markets, and the inclusion of 2020 statistics is likely to alter the results. Moreover, the massive fiscal measures undertaken in many countries and supported by accommodative monetary policies prevented economies to see the full impact of the crisis, in particular on financial institutions. In order to control for these specific circumstances, a binary variable („C19”) equal to 1 in 2020 and 0 otherwise is added to the model.

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		-

Source: Authors' summary.

To avoid any kind of endogeneity bias, as well as to fulfil 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.

**2.5. The Model**

In order to explain risk of potential distress in the insurance sector, the study relies on a binomial logit approach with company fixed effects. The inclusion of company fixed effects allows to control for unobserved characteristics of insurance companies in the sample that have yet an effect on the probability of falling into a distress period. This allows identifying those indicators that positively or negatively affect the likelihood of distress.

In a first stage, the primary interest is to exclusively capture the effects of macroeconomic variables on the probability of distress signalling. Therefore, the simple logit panel regression can be expressed as follows:

$$Prob(D_{it} = 1) = \frac{e^{(\beta X_{t-1} + \alpha_{i,t-1})}}{1 + e^{(\beta X_{t-1} + \alpha_{i,t-1})}} \quad (1)$$

where  $Prob(D_{it} = 1)$  is the probability that company  $i$  at time  $t$  is in a state of distress and  $\alpha_{i,t-1}$  stands for company fixed effects. The vector  $X_t$  contains the set of different independent macroeconomic variables presented in the previous paragraph. As highlighted in Table 1, our analysis will focus both on GDP and on the components of GDP as possible determinants of insurers' distress. Indeed, if economic output had a statistically significant effect on the likelihood of distress, it will be useful to further investigate by which components of GDP it is mainly driven.<sup>8</sup> Additionally, if insurance is considered as a saving vehicle for individuals, it is possible to isolate households' disposable income from consumption.<sup>9</sup> Throughout the paper, the following models are considered – the model containing GDP, the model containing GDP components instead and the model including household disposable income. In a second stage, company-specific indicators are included. This allows to investigate whether macroeconomic variables have any significant impact on a crisis signalling.

$$Prob(D_{it} = 1) = \frac{e^{(\beta X_{t-1} + \gamma Z_{i,t-1} + \alpha_{i,t-1})}}{1 + e^{(\beta X_{t-1} + \gamma Z_{i,t-1} + \alpha_{i,t-1})}} \quad (2)$$

In this case, 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.

In the following sections dealing with empirical analyses, the paper will show results for different specifications of the model (2) including intermediate calculations (e.g. display results for company-specific indicators alone). In this respect, those models should be understood as indicative to see signs and statistical significance of single indicators. Therefore, they should be treated as a robustness check rather than the crucial part of our analysis.

### 3. 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

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<sup>8</sup> GDP components taken into account are: consumption, investment, government expenditure, imports and exports.

<sup>9</sup> The correlation between consumption and disposable income is 0.7.

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 unfavourable event.

As highlighted in Section 2, the model (2) seeks to evaluate indicators at both the macro and micro level. Indeed, the underlying aim of the article is to combine company-specific factors with macroeconomic indicators. In this respect, given the high exposure of insurers to macroeconomic development (e.g. Dorofiti and Jakubik, 2015), standalone accounting indicators are not enough to explain probability of insurance sector's distress. Moreover, while there is an elaborated view on the relationship between growth and insurance profitability, it is harder to claim that specific balance sheet items may lead to a systemic crisis in the sector with certainty. In other words, stability at the individual level, does not necessarily imply stability at the system-wide level. Therefore, first, we evaluate standalone macroeconomic figures (models 1, 2 and 3 in Table 2) and then, we combine them with company-specific factors (Model 4 in Table 3). Models 5, 6 and 7 in Table 3 are just indicative for the direction and magnitude of the coefficients when macroeconomic factors are not included. Hence, we do not carry out a performance evaluation for those models.

The results of the model including only macroeconomic variables (Table 2) 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 suggesting that a potential overheating associated with higher GDP growth and inflation might lead to a systemic crisis with impact on insurers EIOPA (2017b). Although, the effect of the mentioned macroeconomic variables is quite intuitive, it is less obvious for interest rates. On one side, the low interest environment put a lot of pressure on insurers' profitability and solvency in the medium to long-term horizon due to a typically negative duration mismatch and high level of guarantees for life insurers. On the other side, a significant increase of interest rate might potentially increase lapses and negatively influence balance sheets of non-life insurers due to their typically positive duration gap (EIOPA, 2017a; 2021). Moreover, increase in interest rate is usually associated with overheating and monetary policy tightening. Both mentioned transmission channels

are also reflected in the EIOPA Risk Dashboard (EIOPA, 2017b). Our empirical results suggest that the second transmission channel is more relevant for a one-year horizon with a potential to detect systemic distress in the insurance sector a year ahead. Although, the first transmission channel could be crucial in longer-term horizon, it seems to be rather slow-burning risk that does not materialize in one year horizon with a significant likelihood.

When splitting down GDP into its components, extreme crisis episodes are more likely to follow fast-growing consumption and/or disposable income and investments. This is in line with the existing literature on early warning system (e.g. Borio and Drehmann, 2009). Finally, the employed dummy to control for the effect of COVID-19 crisis seem play important role suggested by positive highly significant coefficients for all tested models.

Table 2  
EWS Model with Macroeconomic Variables Only

	(1) Distress	(2) Distress	(3) Distress
GDP	0.423* (0.157)		
Inflation	1.663*** (0.242)	2.395** (0.398)	1.906*** (0.277)
Long term IR	0.612* (0.313)	0.692** (0.313)	0.395 (0.352)
Government expenditure		-0.549 (0.344)	0.0161 (0.287)
Household disposable income			0.662** (0.308)
Investment		0.027 (0.075)	0.132* (0.076)
Export		-0.099 (0.119)	-0.077 (0.119)
Import		-0.024 (0.130)	0.033 (0.124)
Consumption		1.679*** (0.481)	
C19	4.326*** (0.749)	5.397*** (1.328)	3.998*** (1.093)
Number of observations	544	544	544

Note: Standard errors in parentheses, \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01.

Source: Authors' calculations.

The combination of macroeconomic and company level data shows that GDP, inflation and interest rate maintain their sign and statistical significance (Table 3). Compared to our results, the significance of macroeconomic variables for the study conducted by Eling and Jia (2018) was not robust cross different specifications. For real GDP growth, they even obtained different signs for different specifications. It could be explained by the fact that they employed data sample covering

shorter time period (2006 – 2013) compared to ours sample (2004 – 2020). Moreover, data sample employed in (Eling and Jia, 2018) contains more granular company specific data.

Table 3

**EWS Model with Macroeconomic and Company Specific Variables**

	(4) Distress	(5) Distress	(6) Distress	(7) Distress	(8) Distress
GDP	0.347* (0.177)		0.370** (0.156)		0.316* (0.164)
Inflation	1.432*** (0.280)		1.542** (0.239)		1.524*** (0.258)
Long term IR	0.733* (0.395)		0.655** (0.328)		0.758** (0.344)
Price-to-earnings ratio	-0.003 (0.010)	-0.003 (0.005)	-0.002 (0.008)		
Price-to-book value	-0.390* (0.234)	-0.853*** (0.263)	-0.307 (0.265)		
ROA	0.057 (0.154)	0.152 (0.111)			
ROE	-0.030* (0.017)	-0.0793*** (0.019)			
CF to net income	-0.005 (0.018)			0.0032 (0.0120)	-0.00106 (0.0162)
Net premia	0.011 (0.014)			0.0136 (0.0105)	0.0126 (0.0129)
Operating expenses <sup>10</sup>	0.001* (0.001)			0.001* (0.001)	0.001 (0.001)
Underwriting costs	0.001 (0.005)			0.004 (0.004)	0.002 (0.005)
C19	3.552*** (0.869)	0.841* (0.478)	4.101*** (0.738)	1.207*** (0.398)	4.236*** (0.749)
Number of observations	430	528	521	473	447

Note: Standard errors in parentheses, \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01.

Source: Authors' calculations.

Although the coefficient is quite small in terms of weight, extensive operating expenses costs increase the probability of insurer's distress. A drop in return on equity and price-to-book value that can be interpreted as a proxy for financial performance (hence for potential 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. This is in line with (Eling and Jia, 2018) as well as with the assumption that changes in equity valuations could serve as one of macroprudential indicators that could be used to assess the exposure of the insurance sector to economy-wide factors (IAIS, 2021). Moreover, EIOPA Risk Dashboard employs return on equity to assess profitability

<sup>10</sup> Please note that standard errors are roughly half of the estimated coefficients that are significant at 10 significance level, the equal values reported are driven by rounding.

and solvency risks (EIOPA, 2017b). Similarly, as Eling and Jia (2018), contrary to other existing studies, we link the mentioned indicators quantitatively to the likelihood of insurance sector distress. Overall results covering 17-year period show that both macroeconomic and balance sheet indicators could provide an early warning signal on a distress in the European insurance sector.

#### 4. Model Performance Evaluation

There are three performance criteria commonly used to compare logit EWS models: overall accuracy, sensitivity and specificity (Candelon et al., 2012 and Sevim et al., 2014).<sup>11</sup> These measures are helpful to evaluate an in-sample predictive ability, which allows to identify how the model minimizes Type I and Type II errors, as well as its accuracy in correctly predicting distress or correctly detecting non-distress episodes overall. This task is successfully achievable by figuring out the costs associated to policymakers failing to signal a crisis and those to taking excessive precautionary measures once crisis is wrongly spotted by the model.

In the absence of a policymaker utility function, priority is given to the correct detection of crisis episodes.<sup>12</sup> The cut-off value is set in order to correctly predict the proportion of episodes of crises with respect to the total observations.<sup>13</sup> By construction, this coincides with 10%, representing the share of observations labelled as distress events.

As already explained in previous sections, primary interest is given to the 3 most representative models (1, 3 and 4). The resulting statistics in Table 5 highlight the valuable capacity of the models to correctly classify events of distress. Indeed, around 83% of the observed events of distress are accurately predicted on average. The three models have a valid predictive precision of at least 70% for true positives (sensitivity), which is even stronger for true negatives (at least 80% specificity). For the model with aggregate GDP (1), with decomposed GDP (3) and with company specific variables (4), there is at least an 80% overall accuracy score. Given the pure informative nature of models (5) – (8), it is not necessary to run evaluation on those.

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<sup>11</sup> Accuracy measures the proportion of correctly classified events, showing a general probability that the model can correctly classify. Sensitivity (true positive rate) and specificity (true negative rate) respectively measure the ability of the model to correctly classify episodes of distress and the correct classification of tranquil periods. Traditional credit-scoring notions of sensitivity and specificity are also laid down by the Basel Committee on Banking Supervision (2005).

<sup>12</sup> This is based on the assumption of Kaminsky and Reinhart (1999) that a non-identified crisis is costlier than undertaking safeguarding measures in case of a false alarm.

<sup>13</sup> 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.

**Table 4**  
**Post-Estimation Statistics**

<b>Model</b>	<b>(1)</b>	<b>(3)</b>	<b>(4)</b>
Sensitivity	73.75	72.50	70.69
Specificity	82.97	89.66	81.65
Overall Accuracy	81.62	87.13	80.22

*Source:* Authors' calculations.

Given that sensitivity and specificity measures rely on a biased choice of the threshold probability that triggers a crisis, a more valuable tool to assess the performance of a logit model is the Receiving Operator Characteristics (ROC) Curve that is also used as evaluation tool by Drehmann and Juselius (2014) and Vidal-Abarca et al. (2015). ROC displays the ratio of true distress signals (sensitivity) over false alarms (1-specificity). 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 cut-off point. 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.<sup>14</sup>

The AUROC scores for the models employed in this study shows that even when controlling for company specific factors, the performance of the model does not deteriorate. The rate of correctly signalled crisis is kept quite high, with the magnitude of AUROC scoring between the range of 0.84 – 0.88 (Table 5).

**Table 5**  
**Model Performance Comparison<sup>15</sup>**

<b>Model</b>	<b>90th Percentile</b>
AUROC (1)	0.85
AUROC (3)	0.88
AUROC (4)	0.84

*Source:* Authors' calculations.

<sup>14</sup> AUROC = 1 corresponds to perfect classification; AUROC = 0 corresponds to random guess.

<sup>15</sup> 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.

The overall empirical results suggest that our model could complement the existing elements of financial stability assessment frameworks for insurance sectors. Together with the relevant macroprudential indicators (IAIS, 2021) and EIOPA Risk Dashboard (EIOPA, 2017b), the model could be employed to monitor financial stability in the European insurance sector.

## **Conclusion**

This paper 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 companies with yearly data covering years 2004 – 2020. 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, fast-growing consumption and/or disposable income and investments 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 or a drop in return on assets and price-to-book value 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 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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