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Fabrizio Cipollini, Alessandro Giannozzi, Fiammetta Menchetti, Oliviero Roggi

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The Beauty Contest between Systemic and Systematic Risk Measures: Assessing the Empirical Performance

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Abstract

To assess the empirical performance of systemic and systematic risk measures and to face some legitimate concerns in literature regarding the connections between those indicators, we investigate how the state (distressed or not) of a financial company at a given date is related to the corresponding risk indicators. Based on a combination of univariate and multivariate Cox regressions, our approach is applied to 2006-2010 data of 171 listed US financial companies (grouped in two subsamples, S&P and Non-S&P), on which we estimate different versions of nine popular systematic and systemic risk measures, along with leverage as control variable.

Results reveal a strong prevalence of systemic measures and leverage over systematic ones, especially when the time distance between the indicator and the event tends to increase. For the S&P companies, a combination of SRisk and leverage provides a considerable improvement over the best stand-alone indicators, while Expected Shortfall emerges as the only systematic measure providing some information in addition to SRisk and leverage for Non-S&P companies.

Keywords: Systemic and Systematic risk, Cox model, Lasso penalization

JEL codes: G01, G21

1 Introduction

The 2007-2009 financial crisis highlighted the need for appropriate measures of systemic risk to provide a timely identification of the Systemically Important Financial Institutions (SIFIs) and to anticipate potential threats to the stability of the whole financial system.

The literature is far from a consensus on the definition of systemic risk. Sheldon and Maurer (1998) define it as the likelihood that the failure of one bank will trigger a chain reaction that causes other financial institutions to fail, the so-called "domino effect". Along the same line, Kaufmann (1996, p. 3) views systemic risk as the probability that cumulative losses occur and ignite "a series of successive losses along a chain of institutions or markets". These contributions focus on chain reactions and interbank loans, while others concentrate on contagion (De Bandt and Hartmann, 2000), information flows (Mishkin, 2007), correlated defaults and liquidity spirals (Billio *et al.*, 2012; Adrian and Brunnermeier, 2016), spillover effects and externalities (IMF,BIS,FSB, 2009). From these different views, systemic risk emerges as a multi-faceted concept related to many different mechanisms that are difficult to incorporate in a unique and generally accepted definition and measure (c.f. the survey in Benoit *et al.* (2017)).

An appropriate quantification of systemic risk is anyway crucial for efficient regulation. Given the growing number of systemic risk indicators, this implies that regulators and policymakers need a way to discriminate among them, selecting only those measures that prove to be the "best" at anticipating distress scenarios. In other words, systemic risk measures require empirical validation. However, the assessment of the performance of systemic risk measures is still an open issue. For instance, Brownlees and Engle (2017) perform an empirical validation by connecting systemic risk measures to financial firms' distress, proxied by government assistance. Acharya *et al.* (2017) test the empirical performance of given risk measures to predict: i) the outcomes of the Supervisory Capital Assessment Program (SCAP); ii) the realized equity returns of financial firms during the crisis period; iii) the increase in credit risk estimated from Credit Default Swaps (CDS). Finally, Allen *et al.* (2012) and Giglio *et al.* (2016) validate several systemic risk measures by comparing their ability to predict future macroeconomic shocks as measured by the

Chicago Fed National Activity Index (CFNAI) and its subcomponents.

From a different perspective, Benoit *et al.* (2013, 2017) show that common systemic risk measures are theoretically and empirically related to simple systematic (i.e., market) risk measures, suggesting that indicators of the former type may be not sufficient to quantify systemic risk since they seem to be driven by market risk measures and firms' characteristics. They also highlight that additional research should address this concern.

The aim of this paper is to compare the empirical performance of both systemic and systematic risk measures on an empirical "ground": the distress of financial companies during the 2006-2010 period. In other words, we investigate whether the ex-ante risk measures are able to predict the ex-post distress events in the financial industry, on the idea that such an event represents the most tangible and catastrophic expression of risk for a financial institution with potential systemic and contagion effects[1]. More specifically, we address the following research questions:

1. Considering a set of alternative risk measures, which is the best indicator of the state (distressed or not) of a financial company at a future date?

2. Considering different risk measures, can one of them synthesize the whole risk profile of a company, or is there a combination to use because they hold partially different information?

3. How much does the informativeness of one or more risk measures tend to decay when they grow older?

To answer these questions, we consider three Systematic risk measures (CAPM Beta (Beta), Value-at-Risk (VaR), Expected Shortfall (ES)) and six Systemic risk measures (Marginal Expected Shortfall (MES), Systemic Expected Shortfall (SES), Systemic-Risk

[1] De Bandt and Hartmann (2000) identify two types of systemic events: a broad systemic event is a widespread shock affecting many institutions or markets at the same time, while a narrow systemic event is the failure of a financial institution or a market crash. Following this definition, a good systemic risk measure should be able to predict the distress of individual financial institutions and thus, such events can be used as a ground of the empirical validation of risk measures. The link between systemic risk and financial companies default is also present in Roukny *et al.* (2018) who develop a model to compute the systemic probability of default, in order to study how networks structures can affect systemic risk assessment.

(SRisk), Exposure Conditional-VaR (E-CoVaR), and two connectedness measures proposed respectively by Billio *et al.* (2012) (BGLP-in) and Diebold and Yılmaz (2014) (DY-from)[2], along with leverage (LVG) as control variable. For Beta, VaR, ES, MES, SES, SRisk and E-CoVaR we estimate a *historical-based* and a *model-based* version: we compute the former employing a backward looking, rolling window approach, and we derive the latter from a specific time series model (DCC-GARCH for the first three measures, Copula-GARCH for E-CoVaR).

We estimate the measures for a sample of 171 listed US financial companies (78 S&P and 93 non-S&P companies) among which 29 are classified as "Distressed" (12 S&P and 17 non-S&P) and 142 as "Non-distressed". We run the analysis separately for the two subsamples of S&P and non-S&P financial institutions. The time interval of the analysis, January 2006 - December 2010, includes both a pre-crisis and a post-crisis period.

To investigate the relationship between the risk measures of a company and its state at a given time, we perform a survival analysis using the Cox model. We run three sets of regressions: separate univariate models for each risk measure; multivariate models using a Least Absolute Shrinkage and Selection Operator (Lasso) type penalty; and unpenalized (post-Lasso) multivariate models on the risk measures selected by Lasso. The univariate regressions are useful to check which measure, if considered alone, has the highest predictive power for the state of a company. In contrast, the multivariate models suggest whether different indicators can be used together because they carry (partially) different information. We use a Lasso penalization in the Cox model (the first part of the multivariate analysis) to mitigate the high collinearity between the risk measures: we exploit the fact that, among the correlated covariates, Lasso tends to select those with the highest explanatory power for the dependent. The post-Lasso analysis (second phase of the multivariate analysis) is instead useful as a further check and to get a clearer picture of the results.

To check how much the informational content of a risk measure tends to decay with time, for each measure and version we correlate the state of the financial company at a

[2]Benoit *et al.* (2017) point out that these risk measures received considerable attention in the literature, collecting more than 2,700 citations in the past 5 years.

given date to the risk measures estimated at the same time, one week, one month, three months, and six months before (lags 0, 5, 21, 63, and 126 days, respectively).

We improve upon the existing literature in several ways. First, we complement previous studies (Brownlees and Engle, 2017; Acharya *et al.*, 2017; Allen *et al.*, 2012; Giglio *et al.*, 2016) proposing a different validation methodology to select the best financial risk measures or the best method to estimate a given measure. This allows to check whether different measures provide similar information about the company's risk or, alternatively, they can be employed together because their informational content partially differs. Without pretending to build a default prediction model[3], our study contributes to the debate regarding the empirical validation of risk measures, checking the relative importance of systematic and systemic risk measures along Benoit *et al.* (2017, 2013).

A second contribution is the statistical framework, based on a Cox model in which the risk measures explain the company's distress. We complement this with a suitable integration of univariate and multivariate specifications and, within the latter, by a convenient mix of Lasso-based and traditional formulations to circumvent the high collinearity among the risk measures. This integrated tool provides us with clearer conclusions.[4]

A third contribution lies in the empirical evidence emerging: we validate both systematic and systemic risk measures by showing that each one, on a stand alone basis, is a significant predictor (with the expected sign) of financial companies' distress, with the exception of some connectedness measures; we identify the best measure or the best combination in each group (and across the groups). In addition, we get a clear idea about how the information content provided by a risk measure decays with time.

The paper is organized as follows: Section 2 surveys the most relevant literature; Section 3 describes the risk measures selected for the analysis; Section 4 illustrates the data and the methods to estimate the systematic and systemic risk measures; Section 5 discusses the results of the empirical analysis; Section 6 concludes.

[3]To this aim we should add bank-specific variables (profitability, liquidity, capital ratios) and collect a higher number of default events.

[4]Previous literature rests on Tobit regression (Acharya *et al.*, 2017; Brownlees and Engle, 2017), linear regression (Allen *et al.*, 2012; Acharya *et al.*, 2017; Brownlees and Engle, 2017), and quantile regression (Giglio *et al.*, 2016).

2 Literature Review

This paper is related to the literature on systemic risk measurement and empirical validation of risk measures. Benoit *et al.* (2017) classify the former literature in two categories: the *source-specific approach* and the *global systemic risk measures.*

The *source-specific approach* defines different measures for each source of systemic risk, such as contagion effect (Bayoumi *et al.*, 2007; Elsinger *et al.*, 2006), correlated exposures among financial institutions (Lehar, 2005; Blei and Ergashev, 2014), liquidity spirals (Jobst, 2014; Brunnermeier *et al.*, 2013), and bank runs (Goldstein and Pauzner, 2005). For instance, the ACRISK measure of Blei and Ergashev (2014) synthetizes the system's fragilities due to asset commonality, one of the major causes of correlated exposures. Bayoumi *et al.* (2007) develop a measure of contagion based on the relationship between the correlations of equity markets across countries and their geographical distance. Brunnermeier *et al.* (2013) tackles the buildup of banks' exposures to liquidity crises, proposing the Liquidity Mismatch Index (LMI) defined as the cash-equivalent value of assets and liabilities in each state of the world at a future date. Summarizing, the *source-specific approach* allows a detailed representation of the multi-facets nature of systemic risk but, on the other hand, it can lead to fragmentation in regulatory actions and tools.

In contrast, the second approach to systemic risk measurement aims to define *global systemic risk measures* that synthesize the entire contribution of a financial institution to systemic risk in a single indicator. Prominent examples are MES and SES (Acharya *et al.*, 2012), SRisk (Brownlees and Engle, 2017) and CoVaR (Adrian and Brunnermeier, 2016). Although, strictly speaking, they do not measure systemic risk, we include in this group also some indices of *connectedness* among financial institutions proposed by Billio *et al.* (2012) and Diebold and Yılmaz (2014).[5] Since they summarize the total contribution of a financial institution to systemic risk in a single number, global systemic risk measures may help regulator to identify the SIFIs. More generally, because of their market-based

[5]"By definition, systemic risk involves the financial system, a collection of interconnected institutions that have mutually beneficial business relationships through which illiquidity, insolvency, and losses can quickly propagate during periods of financial distress.", Billio *et al.* (2012, p. 536). We label the connectedness measures used in what follows as BGLP-in and DY-from (see Section 3.2 for details). We thank an anonymous referee for the suggestion to add also connectedness measures to the analysis.

nature, they may provide a timely information to recognize distress situations that may lead to systemic events. According to the aim of this study, we focus on global systemic risk measures.

Benoit *et al.* (2017) emphasize the role of empirical validation as the only way to make some insightful selection among the increasing number of systemic risk measures. Brownlees and Engle (2017) assess the empirical performance of SRisk by showing that it is a predictor of the capital injections received from the FED during the crisis[6]. Wu and Zhao (2014) propose a default model that links bank failures to systemic risk, as measured by several indicators (SRisk, CoVaR, Distressed Insurance Premium, LIBOR-OIS spread, trailing 12-month returns from bank stocks). Acharya *et al.* (2012) show that MES is able to predict: i) the outcomes of the SCAP stress test; ii) the realized ex-post equity returns (realized-SES) during the financial crisis; iii) the ex-post CDS returns during the crisis[7]. Oh and Patton (2018) use a dynamic copula model to estimate and check the empirical performance of two systemic risk measures, the joint probability of distress and the expected proportion in distress. Finally, Allen *et al.* (2012) and Giglio *et al.* (2016) perform empirical validation of several systemic risk measures by assessing their ability to predict macroeconomic downturns. Allen *et al.* (2012) propose a market-based macro-level systemic risk measure, the CATFIN, and perform empirical validation by studying its ability to forecast macroeconomic shocks as proxied by the CFNAI Index, the growth rate of US GDP, the industrial production and the unemployment rate. Giglio *et al.* (2016) compare 19 systemic risk measures in forecasting future macroeconomic downturns as measured by the CFNAI Index and its subcomponents.

None of the aforementioned studies investigates the link between financial companies' distress and systematic risk measures[8]. However, Benoit *et al.* (2013, 2017) show that

[6]From a technical point of view, the authors use a Tobit model in which the dependent variable is the FED capital injection, evaluated as the maximum level of borrowings for the financial companies that accessed the federal programs

[7]The authors identify the 5% smallest returns of an equally weighted portfolio of CDS of 40 financial firms, and then compute the CDS return of each firm in the corresponding days. This measure represents a measure of MES based on CDS returns (CDS-MES). Then, they regress it against realized equity returns and against realized CDS returns.

[8]To be precise, the cited papers use firms' Beta (Acharya *et al.*, 2012; Allen *et al.*, 2012) and ES (Acharya *et al.*, 2012; Brownlees and Engle, 2017) only as control variables. They do not focus specifically on systematic risk measures nor they aim to identify the "best" measure in each group.

global systemic risk measures are both theoretically and empirically related to simple market risk measures and firm characteristics, suggesting that such indices might not be enough to measure systemic risk properly. More specifically, deriving the aforementioned systemic risk measures under a common bivariate GARCH-DCC framework, they show that MES is linearly related to the Dynamic Conditional Beta (dcBeta), SRisk has a tight relationship with the company's leverage and with MES (and thus, to a lesser extent, dcBeta), and CoVaR is related to VaR (especially if the distribution of markets' returns is centered around zero, in which case CoVaR is strictly proportional to VaR, at least under the Adrian and Brunnermeier (2016) approach). They then estimate all such risk measures for a sample of US banks during 2000-2010 and show that the empirical data support the theoretical relationships.

Benoit *et al.* (2013, 2017), however, do not validate the aforementioned risk measures, nor they try to identify the "best" one or the best combination of them. Our paper contributes to this strand of literature by comparing the empirical performance of several systemic risk measures on the distress events during the 2006-2010 period. Moreover, differently from previous studies we compare systemic with systematic risk measures, allowing us to appreciate the relative merits according to Benoit *et al.* (2013, 2017).

3 Selection of Risk Measures

In the empirical analysis of the following sections, we consider three systematic (CAPM Beta, VaR, ES) and six systemic (MES, SES, SRisk, CoVaR, DY-from, BGLP-in) risk measures. Although there is extensive literature on the topic, we summarize them here for ease of reference.

We use the following notation:

- $r_{i,t}$ and $r_{M,t}$ are the daily returns on the i-th company and the market, respectively, at day t, while $r_{f,t}$ is the risk-free return at day t;
- $\mathcal{I}_t$ is the information set available at day t;

- $P_t(\cdot) = P(\cdot|\mathcal{I}_t)$, $E_t(\cdot) = E(\cdot|\mathcal{I}_t)$, $V_t(\cdot) = V(\cdot|\mathcal{I}_t)$, $C_t(\cdot,\cdot) = C(\cdot,\cdot|\mathcal{I}_t)$ denote, respectively, the probability, the expectation, the variance, and the covariance of the argument(s) conditional on the information set.

3.1 Systematic Risk Measures

The **Value at Risk** (VaR) at level α for the i-th company at day t is the α-th quantile of $r_{i,t}$ conditional on the available information, namely

$$P_{t-1}\left(r_{i,t} \leq \mathrm{VaR}_{i,t}^{(\alpha)}\right) = \alpha.$$

The **Expected Shortfall** (ES) at level α for the i-th company at day t is the conditional **left-tail** expectation of $r_{i,t}$, in the sense that

$$\mathrm{ES}_{i,t}^{(\alpha)} = E_{t-1}\left(r_{i,t}\middle|r_{i,t} \leq \mathrm{VaR}_{i,t}^{(\alpha)}\right).$$

The **CAPM Beta** for the i-th company is the covariance between the company's excess return and the market excess return, divided by the variance of the latter,

$$\beta_i = \frac{C\left(r_{i,t} - r_{f,t}, r_{M,t} - r_{f,t}\right)}{V\left(r_{M,t} - r_{f,t}\right)}. \tag{1}$$

We can also interpret this as the slope coefficient of the linear regression of $r_{i,t} - r_{f,t}$ on $r_{M,t} - r_{f,t}$. The **Dynamic Conditional Beta** is the 'dynamic' version of (1), in the sense that the covariance and the variance in the formula are replaced by their conditional counterparts (Engle, 2002),

$$\beta_{t,i} = \frac{C_{t-1}\left(r_{i,t} - r_{f,t}, r_{M,t} - r_{f,t}\right)}{V_{t-1}\left(r_{M,t} - r_{f,t}\right)}. \tag{2}$$

3.2 Systemic Risk Measures

The **Marginal Expected Shortfall** (MES) at level α for the i-th company at time t is defined as:

$$\mathrm{MES}_{i,t}^{(\alpha)} = E_{t-1}\left(r_{i,t}\,\middle|\, r_{M,t} \le \mathrm{VaR}_{M,t}^{(\alpha)}\right).$$

As illustrated by Acharya *et al.* (2017), the term comes from the fact that MES measures the company's contribution to overall risk, expressed by the system $\mathrm{ES}_{M,t}^{(\alpha)}$, when the market is in distress according to the condition $r_{M,t} \le \mathrm{VaR}_{M,t}^{(\alpha)}$.

Acharya *et al.* (2017) also propose **Systemic Expected Shortfall** (SES). Taking $z \in (0,1)$ and denoting with w and a the equities and assets, respectively, the definition of SES is based on the gap $w - za$: a company (or a system) is in distress when the corresponding gap is negative. Accordingly, the SES of the i-th company at time t is the conditional expectation of $w_{i,t} - za_{i,t}$ when the corresponding value for the system, $w_{M,t} - za_{M,t}$, is negative,

$$\mathrm{SES}_{i,t} = E_{t-1}\left(w_{i,t} - za_{i,t}\,|w_{M,t} - za_{M,t} < 0\right).$$

Since this definition is difficult to use in practice, Acharya *et al.* (2017) derive, under some assumptions, the empirical relationship

$$\frac{\mathrm{SES}_{i,t}}{w_{i,t-1}} = \frac{za_{i,t} - w_{i,t-1}}{w_{i,t-1}} + k\,\mathrm{MES}_{i,t}^{(0.05)} + \Delta_{i,t}$$

where: $\Delta_{i,t}$ is an adjustment term with the excess cost of financial distress representing its main part; k, the relative severity, is the ratio between the critical values $\varepsilon_M^{(0.05)}$ (associated with the worst 5% market outcomes) and $\varepsilon_M^{(*)}$ (related to the event $w_{i,t} - za_{i,t} < 0$) of the system shocks ε_M (cf. Acharya *et al.* (2017, pp. 7-17) for the details).[9]

Proposed by Brownlees and Engle (2017), the **Systemic Risk** (SRisk) for the i-th company at time t is defined as its expected Capital Shortfall, over a given horizon, conditionally on a systemic event, identified by a market return between $t+1$ and $t+h$

[9]Since Acharya *et al.* (2017) uses a two-period framework in which $t = 0, 1$, we adapted the notation to this study.

falling below an extreme threshold c:

$$\mathrm{SRisk}_{i,t} = E_t \left(\mathrm{CS}_{i,t+h} \left| r_{M,t+1:t+h} < c \right. \right). \tag{3}$$

The Capital Shortfall (CS) is the capital reserve the firm needs to hold due to regulation and prudential management minus the firm's equity:

$$\mathrm{CS}_{i,t} = k a_{i,t} - w_{i,t} = k \left(d_{i,t} + w_{i,t} \right) - w_{i,t} = k d_{i,t} - (1-k) w_{i,t} \tag{4}$$

where w is the market value of equity, d is the book value of debt, a is the quasi-market value of assets, and k is the prudential capital fraction. When CS is negative, the firm is functioning properly since it means that its equity capital is above the required prudential fraction of its assets; if it is positive, the company is experiencing distress. Replacing (4) in (3) leads to the following expression of SRisk

$$\mathrm{SRisk}_{i,t} = w_{i,t} \left(k \, \mathrm{LVG}_{i,t} + (1-k) \, \mathrm{LRMES}_{i,t} - 1 \right), \tag{5}$$

where LVG is the company's leverage, and LRMES, the Long Run Marginal Expected Shortfall, is the expected multi-period equity return in case of a systemic crisis (aggregate market returns falling below the extreme threshold c).

Proposed by Adrian and Brunnermeier (2016), the CoVaR at time t of j relative to i (both j and i can be an institution or a financial system) is defined as the VaR of j conditional to some event experienced by i

$$P_{t-1} \left(r_{j,t} \leq \mathrm{CoVaR}^{(\alpha)}_{j|*,t} \left| r_{i,t} \in * \right. \right) = \alpha. \tag{6}$$

Typical conditioning events are $r_{i,t} = \mathrm{VaR}^{(0.5)}_{i,t}$ and $r_{i,t} = \mathrm{VaR}^{(\alpha)}_{i,t}$, interpreted, respectively, as i being in a normal situation or in distress. With the same interpretations, Girardi and Ergün (2013) consider instead $r_{i,t} \leq \mathrm{VaR}^{(0.5)}_{i,t}$ and $r_{i,t} \leq \mathrm{VaR}^{(\alpha)}_{i,t}$. This leads to the Delta-CoVaR,

$$\Delta \mathrm{CoVaR}^{(\alpha)}_{j|i,t} = \mathrm{CoVaR}^{(\alpha)}_{j|\alpha,t} - \mathrm{CoVaR}^{(\alpha)}_{j|0.5,t}$$

where, to simplify the notation, the asterisk in (6) is replaced with the VaR-related probability of the conditioning institution. If j refers to a whole system and i to a financial company, the Delta-CoVaR captures the marginal contribution of the j-th company to the overall system risk. Reversing the conditioning and labeling j as M (as in the previous systemic risk measures) yields the Exposure-CoVaR

$$\text{E-CoVaR}^{(\alpha)}_{i|M,t} = \text{CoVaR}^{(\alpha)}_{i|\alpha,t} - \text{CoVaR}^{(\alpha)}_{i|0.5,t},$$

which measures the extent of the effect of a systemic crisis on institution i. As Adrian and Brunnermeier (2016) stresses, this direction of conditioning is more in line with the systemic risk measures defined above.

Within the Systemic Risk indicators we also include some indices of financial *connectedness* proposed by Billio *et al.* (2012) and Diebold and Yilmaz (2015, and references therein). Such measures are constructed using a similar two-stage mechanism: in the first, a pairwise directional (*out* toward *in*) measure is calculated between each couple (i, j) of financial institutions, obtaining a squared *connectedness table*; in the second, such matrix is further synthesized to derive the *in* or *out* degree of connectedness of each institution with the others.[10]

The first stage by Billio *et al.* (2012) is based on Granger causality in returns: for each couple of financial institutions, a bivariate VAR(1) model is estimated on the time series of standardized returns (standardization is obtained dividing each return by the corresponding conditional standard deviation estimated from a GARCH model); the pairwise $i \to j$ measure of connectedness is set to one if i is significant in causing j and to zero otherwise.

The first stage by Diebold and Yilmaz (2015) is instead based on a VAR analysis in volatility: a joint VAR model is estimated on the time series of volatility measures (like the Parkinson (1980) or the Garman and Klass (1980) ranges) of all companies; then the pairwise $i \to j$ measure of connectedness is obtained using a Forecasting Error Variance

[10] The labels *in* and *out* come from Billio *et al.* (2012); with similar meaning, Diebold and Yilmaz (2015) use instead *from* others and *to* others.

Decomposition (FEVD) to evaluate what fraction of h-step forecast error variance of j is due to shocks in i.

As far as the second stage, the cited works present several measures to synthesize the degree of connectedness of a financial institution with the others. Using a principle similar to the choice of E-CoVaR within the CoVaR domain, we selected those expressing the degree of connectedness directed *toward* the institution: the `#In` measure in Equation (15) of Billio *et al.* (2012) and the `from` others measure in the first equation of p. 10 of Diebold and Yilmaz (2015) (such measures are labeled here as BGLP-in and DY-from, respectively).

4 Data and Methodology

4.1 Data

Since systemic risk drivers can be different between major financial institutions and minor banks and, more in general, a different size may impact on companies' degree of connectedness with the rest of the system, we conducted the empirical analysis on two different datasets (labeled S&P and Non-S&P), grouped as follows:[11]

- All the 87 *S&P500* Financials index constituents in 2006. Among them, 7 companies are excluded because they were involved in M&A deals for reasons not directly related to distress or liquidity crisis and 2 due to missing data.[12] Among the remaining 78, 12 are classified as "distressed" according to one of the following criteria:
  - i) the company filed for Chapter 11 bankruptcy protection;[13]
  - ii) the company was acquired by competitors as a private sector solution to their crisis;[14]

[11] To give an idea of the different "nature" of the two groups of companies, the average assets are 198.0 and 8.3 billion USD (median 60.4 and 5.7), respectively, for the S&P and Non-S&P sets at the beginning of 2006.

[12] We excluded from the analysis Archstone-Smith Trust, BBVA Compass Bancshares Inc., Commerce Bancorp, Equity Office Properties Trust, Mellon Financial Corp, Safeco Corp, and Santander Holdings USA Inc. and we have missing data for Realogy Group and Ameriprise Financial Inc.

[13] Ambac Financial Group, CIT Group, Lehman Brothers and Washington Mutual.

[14] Bear Sterns, Countrywide Financial Corp, Merrill Lynch, National City Corp, and Wachovia.

iii) the company was bailed-out by the government.[15]

- All the 329 financial companies in the FDIC official list with assets larger than 2 billion USD as of March 31, 2005. Among them, we excluded private bank holdings and, to avoid double counts, the subsidiaries of listed bank holdings. As above, we also excluded the banks ceasing their activity for reasons other than a crisis or those presenting missing data. Summarizing, the total number of banks in this subsample is 93, of which 17 are classified as *failed* by the FDIC.[16]

Tables 10 and 11 in Appendix list the companies included in the two subsamples. The period of analysis goes from January 2005 to December 2010. We source the daily stock prices and quarterly financial statement data from Bloomberg.

4.2 Estimation of Risk Measures

We use the data to estimate the risk measures listed in Section 3. For each measure (with the exception of the connectedness measures which are presented separately in Section 4.2.3) we consider an *historical-based* (or *static*) and a *model-based* (or *dynamic*) version. The former (indexed by 1) is an historical statistic computed on rolling window data, while the latter (indexed by 2) is produced by a suitable time series model.

4.2.1 Historical-based Estimates

We estimate the *historical-based* version of each risk indicator using a rolling window, backward looking approach (one year window size, day by day roll). To be clear, we use data from Jan. 3, 2005 to Dec. 30, 2005 to derive the risk measure at Jan. 3, 2006; we use data from Jan. 4, 2005 to Jan. 3, 2006 to obtain the risk measure at Jan. 4, 2006; and so on.[17]

[15] AIG and the two GSEs Fannie Mae and Freddie Mac. The two GSE were placed into conservatorship on September 7, 2008, and AIG was classified as a "failure" by the Financial Crisis Inquiry Commission (FCIC).

[16] The complete FDIC list of failed banks is available at `https://www5.fdic.gov/hsob/hsobRpt.asp`

[17] Since we employ an estimation window of one year, we also use 2005 data to set the analysis for the period 2006-2010.

Considering a generic data window of one year (say, from $t-252$ to $t-1$), we estimate the indicators at time t for the i-th company as follows (when not strictly needed, we omit indices i and t to simplify the notation).

- $\widehat{\mathrm{VaR}}_1$ (the VaR at 5%) is the 5-th percentile of the ticker returns.
- $\widehat{\mathrm{ES}}_1$ (the ES at 5%) is the average of the ticker returns below $\widehat{\mathrm{VaR}}_1$.
- $\widehat{\mathrm{Beta}}_1$ (the CAPM Beta) is the slope coefficient of the linear regression of the ticker returns on the corresponding market returns.
- $\widehat{\mathrm{MES}}_1$ (the MES at 5%) is the average of the ticker returns when the market returns fall below their VaR at 5% (Acharya *et al.*, 2017).
- We derive $\widehat{\mathrm{SES}}_1$ (the SES at 5%) from $\widehat{\mathrm{MES}}_1$ using the relationship

$$\widehat{\mathrm{SES}} = 0.02 - 0.15 \cdot \widehat{\mathrm{MES}} - 0.04 \cdot \mathrm{LVG} \tag{7}$$

  as in Acharya *et al.* (2017) (see also Brownlees and Engle (2017)). We compute LVG, the company's leverage, using the standard approximation based on the quasi-market-value of assets,

$$\mathrm{LVG} = \frac{\text{Quasi-MV of assets}}{\text{MV equity}} = \frac{\text{BV assets} - \text{BV equity} + \text{MV equity}}{\text{MV equity}}$$

  where MV and BV denote the market and book values, respectively. Since accounting data are available on a quarterly basis, we assume constant BV variables in this period. We instead calculate MV equity for each day as the daily stock price times the number of shares outstanding.

- Following Brownlees and Engle (2017), we compute $\widehat{\mathrm{SRisk}}_1$ (the SRisk at 5%) using Equation (5), where we assume the prudential capital ratio k equal to 8% and we estimate the long run MES using the approximation

$$\widehat{\mathrm{LRMES}} \approx 1 - \exp(18 \cdot \widehat{\mathrm{MES}}) \tag{8}$$

(regarding the choice of k and the approximation (8) see Acharya *et al.* (2012)).

- We calculate E-$\widehat{\text{CoVaR}}_1$ (the Exposure CoVaR at 5%) according to Adrian and Brunnermeier (2016). The crucial ingredient is a quantile regression, for $\alpha = 0.05$, of the company's returns against the market's returns to get estimates of the intercept and slope coefficients ($\widehat{\beta}_0^{(0.05)}$ and $\widehat{\beta}_1^{(0.05)}$, respectively). We can then estimate the CoVaR as
$$\widehat{\text{CoVaR}}_{i|\beta,t}^{(0.05)} = \widehat{\beta}_0^{(0.05)} + \widehat{\beta}_1^{(0.05)} \widehat{\text{VaR}}_{M,t}^{(\beta)} \tag{9}$$
for any $\beta \in (0,1)$. Using (9) for $\beta = 0.05$ and $\beta = 0.5$ allows us to compute E-$\widehat{\text{CoVaR}}_1$ as
$$\widehat{\text{CoVaR}}_{i|0.05,t}^{(0.05)} - \widehat{\text{CoVaR}}_{i|0.5,t}^{(0.05)}. \tag{10}$$

4.2.2 Model-based Estimates

We estimate the *model-based* version of the risk indicators using specific time series models: a Copula-GARCH (with a Student's-T copula) for CoVaR; and a DCC-GARCH (with a Student's-T multivariate distribution) for all remaining indicators but the connectedness ones (for VaR and ES we use only the output of the GARCH part). All GARCH estimates are obtained assuming a Student-T distribution of errors, a constant conditional mean level, and applying separately both GJR-GARCH(1,1) and T-GARCH(1,1) to account for possible asymmetric effects.[18]

We use the following notation:

- $\mu_{i,t}$, $\sigma_{i,t}$ are the conditional mean and volatility, respectively, of the return on the i-th company at day t; an M in place of i indicates the same quantity referring to the market return;[19]

- $\rho_{i,M,t}$ denotes the conditional correlation between the i-th company and the market

[18]From the theoretical point of view, all model-based measures referred to time t are conditioned only on the information available at that time. From an empirical perspective, however, such models depends on coefficients that have to be estimated: since, for computational simplicity, we calibrated all parameters on the full sample, this makes the empirical evaluation of such measures to depend on all observations, at least in a small extent. All models are estimated using the `R` package `rmgarch` (Ghalanos, 2019).

[19]Although we assume a constant conditional mean in the GARCH specifications, we use the generic notation $\mu_{i,t}$ and $\mu_{M,t}$.

at day t.

We estimate the indicators at time t for the i-th company as follows (when not strictly needed, we omit indices i and t to simplify the notation).

- $\widehat{\mathrm{VaR}}_2$ (the VaR at 5%) is

$$\widehat{\mu}_{i,t} + \widehat{\sigma}_{i,t}\widehat{z}_i^{(0.05)}$$

where $\widehat{z}^{(0.05)}$ is the 5-th percentile of the GARCH standardized residuals of the i-th ticker.

- $\widehat{\mathrm{ES}}_2$ (the ES at 5%) is

$$\widehat{\mu}_{i,t} + \widehat{\sigma}_{i,t}\widehat{\mathrm{ES}}_i^{(0.05)}$$

where $\widehat{\mathrm{ES}}_i^{(0.05)}$ is the mean of the GARCH standardized residuals of the i-th ticker when they are below their 5-th percentile.

- $\widehat{\mathrm{Beta}}_2$ (the Dynamic Conditional Beta) is

$$\widehat{\rho}_{i,M,t}\frac{\widehat{\sigma}_{i,t}}{\widehat{\sigma}_{M,t}}.$$

- We compute $\widehat{\mathrm{MES}}_2$ (the MES at 5%) as follows. Using the output of the estimated DCC-GARCH, we compute vectors of pseudo-returns at time t for both the ticker and the market,

$$\widetilde{\boldsymbol{r}}_{i,t} = \widehat{\mu}_{i,t} + \widehat{\sigma}_{i,t}\widehat{\boldsymbol{z}}_i \qquad \widetilde{\boldsymbol{r}}_{M,t} = \widehat{\mu}_{M,t} + \widehat{\sigma}_{i,t}\widehat{\rho}_{i,M,t}\widehat{\boldsymbol{z}}_i + \widehat{\sigma}_{M,t}(1-\widehat{\rho}_{i,M,t}^2)^{1/2}\widehat{\boldsymbol{z}}_M$$

where $\widehat{\boldsymbol{z}}_i$ and $\widehat{\boldsymbol{z}}_M$ denote the whole vectors of the orthonormal residuals for the ticker and the market, respectively.[20] Using the pseudo-returns $\widetilde{\boldsymbol{r}}_{M,t}$, we can estimate

[20]The *orthonormal* residuals are $\widehat{\boldsymbol{z}}_t = \widehat{\boldsymbol{\Sigma}}_t^{-1/2}(\boldsymbol{x}_t - \widehat{\boldsymbol{\mu}}_t)$, where $\widehat{\boldsymbol{\mu}}_t$ and $\widehat{\boldsymbol{\Sigma}}_t$ indicate the estimated conditional mean and the variance-covariance matrix of the ticker and market returns at time t. In matrix form, we can then express the pseudo-residuals as

$$\widetilde{\boldsymbol{r}}_t = \widehat{\boldsymbol{\mu}}_t + \widehat{\boldsymbol{\Sigma}}_t^{1/2}\widehat{\boldsymbol{z}}_t.$$

The basic idea of this approach is to use the estimated orthonormal residuals to reconstruct the variability around the estimated conditional moments at time t and to use it to estimate MES.

the corresponding market VaR at 5% at time t, $\widehat{\mathrm{VaR}}_{M,t}^{(0.05)}$; we then obtain $\widehat{\mathrm{MES}_2}$ by averaging the values into $\widetilde{\boldsymbol{r}}_{i,t}$ corresponding to the elements of $\widetilde{\boldsymbol{r}}_{M,t}$ less than $\widehat{\mathrm{VaR}}_{M,t}^{(0.05)}$.

- We obtain $\widehat{\mathrm{SES}_2}$ (the SES at 5%) and $\widehat{\mathrm{SRisk}_2}$ (the SRisk at 5%) from $\widehat{\mathrm{MES}_2}$ exactly as we derive $\widehat{\mathrm{SES}_1}$ and $\widehat{\mathrm{SRisk}_1}$ from $\widehat{\mathrm{MES}_1}$.

- We compute $\widehat{\text{E-CoVaR}_2}$ (the Exposure CoVaR at 5%) following Reboredo and Ugolini (2015). The estimated Copula-GARCH model between the ticker and the market delivers estimates, at each t, of the conditional copula function, $C(\cdot,\cdot|\mathcal{I}_{t-1})$, and the marginal c.d.f., $F(\cdot|\mathcal{I}_{t-1})$, of the company's standardized errors. For any $\beta \in (0,1)$, this allows us to estimate the CoVaR as

$$\widehat{\mathrm{CoVaR}}_{i|\beta,t}^{(0.05)} = \widehat{\mu}_{i,t} + \widehat{\sigma}_{i,t}\widehat{F}^{-1}(u_{i,t}^{(\beta)}|\mathcal{I}_{t-1})$$

where the quantile $u_{t,i}^{(\beta)}$ is such that $\beta \cdot 0.05 = \widehat{C}(u_{t,i}^{(\beta)}, 0.05|\mathcal{I}_{t-1})$. Using the above relationship for $\beta = 0.05$ and $\beta = 0.5$ allows us to compute $\widehat{\text{E-CoVaR}_2}$ as in Equation (10).

4.2.3 Estimates of the Connectedness Measures

The models needed to get the financial connectedness measures (Section 3.2) are estimated using a rolling window, backward looking approach (one year window size, day by day roll) similar to the historical-based estimates (Section 4.2.1); each window gives the matrix of pairwise connections referred to its final day.

- The standardized returns needed by the Granger causality analysis to compute BGLP-in, are obtained dividing the original returns by the conditional standard deviations estimated using the GARCH-based estimates of Section 4.2.2.

- The joint VAR model needed to derive DY-from is estimated using the logarithm of the Garman and Klass (1980) range as measure of volatility. The huge number of assets, however, required specific remedies to avoid model over parameterization.

To this aim we modeled log-volatilities using the penalized-VAR approach described by Nicholson *et al.* (2018).[21] Following Diebold and Yilmaz (2015), the FEVD is done using the generalized approach by Pesaran and Shin (1998); the forecasting horizon h, needed in the FEVD to compute the pairwise directional connections, is taken equal to 10 days (about two weeks).

4.3 Survival Analysis

Researchers can use survival models when they aim to investigate the effect of some variables on the time at which an event may take place. In our setting, the "event" is the distress of a financial institution (which may happen or not) and the explanatory variables are the estimated risk measures (which are time-varying because they change daily).

Among the formulations available, we adopt a Cox model with time-varying covariates (Kalbfleisch and Prentice, 2002, ch. 6). Such model specifies the conditional hazard function[22] as

$$\lambda\left(t|\boldsymbol{x}_t\right) = \lambda_0(t)\exp(\boldsymbol{x}_t'\boldsymbol{\beta}),$$

where $\boldsymbol{x}_t$ is a vector of regressors, β is the vector of the corresponding parameters, and $\lambda_0(t)$ is a baseline hazard function which does not depend on the covariates. In our application, $\boldsymbol{x}_t$ denotes a vector of risk measures, which may be taken at a given lag with respect to t. In fact, to check how much their informational content tends to decay with time, we correlated the state of the company at each t to the risk measures estimated at the same time, one week, one month, three months, and six months before (lags 0, 5, 21, 63, and 126 days, respectively). We choose Cox model to exploit its non-parametric flavor, namely the possibility to estimate coefficients without having to specify the baseline

[21] The methodology is implemented in the R-package `BigVAR` (Nicholson *et al.*, 2019) using the `Basic` parameterization. See also Demirer *et al.* (2018) for an analysis of financial connectedness based on a penalized-VAR model.

[22] If T denotes the waiting time until the occurrence of an event of interest, the hazard function $\lambda(t)$ is the probability that the event takes place on the infinitesimal interval $(t, t+\Delta t]$ conditionally to the fact that it did not happen before, in symbols

$$\lambda(t) = P(t < T \leq t + \Delta t | T > t).$$

hazard function.

We run three sets of regression analyses:

- separate univariate models for each risk measure, estimation approach, and lag;
- multivariate models under a Lasso type penalty to reduce the effect of the collinearity among the indicators;
- unpenalized (post-Lasso) multivariate models on the risk measures selected by Lasso.

The univariate regressions are a useful mean to select which measure, if considered alone, has the highest predictive content for the state of the company; the multivariate models, on the other hand, suggest whether different indicators can be used together because they carry (partially) different informational content, allowing us to select the best measures and to estimate their corresponding weights.

Tables 1 and 2, which report Pearson and Spearman correlations between the risk measures in the two subsamples of companies, give a clear idea of their degree of correlation. The high collinearity among the risk measures is an important obstacle to the multivariate analysis: this is why we resort to Lasso.

Adapted to the Cox model by Tibshirani (1997), this method allows model fitting and variable selection at the same time by shrinking the coefficients to zero in a particular way. Considering a Cox-Lasso model with p covariates, whose effect is ruled by a vector of parameters $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_p)$, we estimate such parameters by maximizing a penalized version of the partial log-likelihood, that is,

$$\max_{\boldsymbol{\beta}} \left(\text{partial log-lik} - \lambda \sum_{j=1}^{p} |\beta_j| \right) \tag{11}$$

where $\lambda \geq 0$ is a penalty parameter. For $\lambda = 0$, we obtain the usual Cox model; for $\lambda \to \infty$, we shrink all parameters at zero. λ usually lies between these two extremes. The shrinking property of the method can be better understood by recalling that we can rewrite (11) as

$$\max_{\boldsymbol{\beta}} (\text{partial log-lik}) \qquad \text{s.t.} \qquad \sum_{j=1}^{p} |\beta_j| \leq \tau \tag{12}$$

Table 1: **S&P subsample**. Pearson (upper triangle) and Spearman (lower triangle) correlations between risk measures.

	$Beta_1$	$Beta_2$	VaR_1	VaR_2	ES_1	ES_2	MES_1	MES_2	SES_1	SES_2	$SRisk_1$	$SRisk_2$	E-$CoVaR_1$	E-$CoVaR_2$	DY-from	BGLP-in	LVG
$Beta_1$		0.678	-0.751	-0.511	-0.750	-0.510	-0.740	-0.505	0.662	0.449	0.371	0.332	-0.784	-0.497	0.224	0.026	0.291
$Beta_2$	0.779		-0.676	-0.647	-0.665	-0.641	-0.628	-0.633	0.622	0.541	0.304	0.317	-0.680	-0.632	0.135	0.061	0.334
VaR_1	-0.833	-0.688		0.673	0.978	0.671	0.948	0.655	-0.838	-0.567	-0.315	-0.274	0.980	0.667	-0.039	0.011	-0.356
VaR_2	-0.695	-0.682	0.819		0.715	0.993	0.668	0.964	-0.710	-0.750	-0.263	-0.301	0.667	0.965	-0.026	-0.068	-0.405
ES_1	-0.825	-0.682	0.987	0.827		0.719	0.953	0.691	-0.870	-0.609	-0.318	-0.278	0.973	0.711	-0.022	-0.009	-0.391
ES_2	-0.689	-0.678	0.816	0.995	0.827		0.660	0.959	-0.726	-0.764	-0.252	-0.289	0.662	0.975	-0.005	-0.080	-0.430
MES_1	-0.821	-0.668	0.954	0.794	0.953	0.791		0.681	-0.824	-0.541	-0.346	-0.298	0.951	0.664	-0.114	0.044	-0.303
MES_2	-0.702	-0.697	0.801	0.972	0.808	0.973	0.807		-0.691	-0.744	-0.286	-0.327	0.650	0.967	-0.070	-0.070	-0.374
SES_1	0.793	0.665	-0.879	-0.760	-0.886	-0.764	-0.917	-0.777		0.791	0.401	0.384	-0.828	-0.713	0.017	0.005	0.643
SES_2	0.687	0.665	-0.727	-0.864	-0.742	-0.873	-0.744	-0.892	0.876		0.312	0.340	-0.554	-0.752	-0.006	0.056	0.898
$SRisk_1$	0.608	0.526	-0.605	-0.553	-0.618	-0.561	-0.625	-0.570	0.809	0.778		0.965	-0.330	-0.260	0.147	-0.029	0.244
$SRisk_2$	0.548	0.520	-0.520	-0.591	-0.536	-0.603	-0.533	-0.613	0.737	0.823	0.950		-0.285	-0.297	0.141	-0.021	0.257
E-$CoVaR_1$	-0.845	-0.691	0.987	0.820	0.983	0.815	0.956	0.805	-0.879	-0.729	-0.606	-0.522		0.653	-0.078	0.031	-0.341
E-$CoVaR_2$	-0.665	-0.665	0.795	0.965	0.811	0.976	0.791	0.973	-0.767	-0.879	-0.563	-0.603	0.794		-0.003	-0.073	-0.407
DY-from	0.292	0.204	-0.173	-0.135	-0.153	-0.118	-0.240	-0.192	0.256	0.205	0.234	0.192	-0.197	-0.122		-0.159	-0.054
BGLP-in	-0.002	0.042	0.087	0.005	0.080	-0.003	0.117	0.007	-0.110	-0.010	-0.036	0.011	0.095	0.011	-0.192		0.032
LVG	0.385	0.367	-0.324	-0.349	-0.346	-0.369	-0.349	-0.368	0.646	0.705	0.749	0.766	-0.328	-0.392	0.149	-0.017	

Table 2: **Non-S&P subsample**. Pearson (upper triangle) and Spearman (lower triangle) correlations between risk measures.

	$Beta_1$	$Beta_2$	VaR_1	VaR_2	ES_1	ES_2	MES_1	MES_2	SES_1	SES_2	$SRisk_1$	$SRisk_2$	E-$CoVaR_1$	E-$CoVaR_2$	DY-from	BGLP-in	LVG
$Beta_1$		0.490	-0.339	-0.256	-0.338	-0.252	-0.396	-0.258	0.159	0.139	0.459	0.439	-0.395	-0.287	0.170	-0.143	0.108
$Beta_2$	0.526		-0.361	-0.394	-0.356	-0.391	-0.367	-0.481	0.163	0.174	0.372	0.408	-0.379	-0.487	0.083	-0.066	0.113
VaR_1	-0.380	-0.338		0.774	0.977	0.756	0.848	0.605	-0.586	-0.544	-0.562	-0.525	0.971	0.653	0.150	0.070	-0.482
VaR_2	-0.295	-0.372	0.812		0.799	0.991	0.631	0.844	-0.557	-0.586	-0.484	-0.539	0.737	0.888	0.129	-0.003	-0.491
ES_1	-0.351	-0.318	0.983	0.817		0.790	0.845	0.623	-0.593	-0.556	-0.560	-0.526	0.959	0.683	0.162	0.058	-0.492
ES_2	-0.285	-0.366	0.803	0.994	0.814		0.608	0.824	-0.560	-0.591	-0.477	-0.532	0.717	0.881	0.146	-0.027	-0.499
MES_1	-0.378	-0.321	0.908	0.740	0.900	0.725		0.653	-0.388	-0.333	-0.585	-0.519	0.894	0.637	-0.066	0.220	-0.254
MES_2	-0.290	-0.467	0.705	0.912	0.703	0.906	0.717		-0.337	-0.382	-0.471	-0.545	0.619	0.937	-0.067	0.109	-0.254
SES_1	0.353	0.328	-0.936	-0.801	-0.943	-0.799	-0.911	-0.705		0.979	0.274	0.272	-0.518	-0.409	-0.168	0.068	0.975
SES_2	0.317	0.406	-0.818	-0.936	-0.827	-0.941	-0.750	-0.879	0.878		0.255	0.272	-0.471	-0.448	-0.166	0.083	0.991
$SRisk_1$	0.391	0.368	-0.825	-0.713	-0.836	-0.721	-0.780	-0.630	0.906	0.819		0.943	-0.582	-0.466	0.059	-0.153	0.198
$SRisk_2$	0.369	0.417	-0.754	-0.818	-0.767	-0.827	-0.681	-0.752	0.833	0.913	0.918		-0.532	-0.530	0.021	-0.111	0.206
E-$CoVaR_1$	-0.391	-0.332	0.981	0.797	0.976	0.787	0.912	0.698	-0.923	-0.798	-0.806	-0.730		0.652	0.078	0.133	-0.403
E-$CoVaR_2$	-0.280	-0.439	0.721	0.936	0.730	0.945	0.696	0.950	-0.726	-0.899	-0.666	-0.784	0.709		0.031	0.051	-0.333
DY-from	0.141	0.114	-0.008	0.022	0.007	0.039	-0.184	-0.137	0.002	-0.060	-0.026	-0.081	-0.041	-0.038		-0.363	-0.183
BGLP-in	-0.105	-0.086	0.207	0.120	0.197	0.096	0.281	0.154	-0.163	-0.083	-0.122	-0.077	0.227	0.103	-0.291		0.103
LVG	0.294	0.316	-0.699	-0.654	-0.715	-0.668	-0.582	-0.515	0.822	0.810	0.854	0.856	-0.671	-0.584	-0.252	-0.007	

where the threshold τ is a monotonically decreasing transformation of λ. The peculiar diamond-shaped constraint region in (12) implies that some coefficients may be constrained at zero, while others may differ.

From the practical point of view, Lasso tends to be quite selective among highly correlated covariates, in the sense that only a few will appear with nonzero estimated coefficients.

A crucial issue in penalized models is the choice of the penalty parameter λ. A typical option is to optimize it using Leave-One-Out Cross Validation (LLOCV, James *et al.* (2014, Section 5.1.2)), but with this model and our dataset, this option is computationally unfeasible. As a viable alternative, we resort to k-fold Cross Validation (k-fold CV, James *et al.* (2014, Section 5.1.3)) with $k = 20$, randomly selecting the observations into the k subsamples but leaving the same allocation across all models. Since, in contrast to LOOCV, the k-fold CV may give somewhat different outcomes in different estimation runs depending on the allocations of the observations in the k subsamples, we checked the stability of the results by repeating all estimates with three different random distributions of the observations in the k sets.

To avoid spurious results and interpretation difficulties, we also constrained the signs of the coefficients of each risk measure such that either one parameter has the expected sign or it is forced to be zero.[23].

All analyses are repeated, shifting the covariates backward by 0, 5, 21, 63, and 126 trading days (broadly corresponding to 'no lag', 'one week', 'one month', 'three months' and 'six months' before), to analyze to what extent the informational content of the risk measures about the state of the company decays with time. Finally, we estimate the

[23]This is automatically done by the software by setting appropriate function arguments. The decision to constrain the sign of the coefficients to what expected a priori has been adopted to get interpretable results. In fact, if the risk measures were uncorrelated, the sign of the respective coefficient in the multivariate analysis would be equal to the univariate. Unfortunately, the risk measures are highly correlated: this implies that in the multivariate model, some can have a sign which is different from the expected one. To be concrete, image that Beta has a significant negative sign: in this case it would be hard to convince a practitioner that "all other risk measures taken fixed, an increase of Beta will tend to reduce risk". In the appendix we also report the unconstrained coefficient estimates of the multivariate analysis. There are cases in which some risk indicators result with a coefficient sign which is different from what expected a priori (i.e. Tables 12 and 13, Non-S&P, with Beta_2 having negative sign, or Table 13, Non-S&P, having MES_1 with positive sign). It is just to avoid troubles in interpreting this kind of results that we preferred to implement sign restrictions in estimation.

multivariate models separately by group of indicators (systematic and systemic), then considering all measures together.[24]

5 Results

This section presents the empirical results obtained by applying the methodology described in Section 4.2 to the data illustrated in Section 4.1. Section 5.1 discusses the outcomes of the univariate Cox regressions; Section 5.2 presents the results of the Cox-Lasso model; the post-Lasso robustness check is shown in Section 5.3. Although we estimated the DCC-GARCH and copula-GARCH models with both GJR-GARCH and T-GARCH specifications, in what follows we discuss only the results of the latter because, in the majority of cases, it provided a better fit to the data in terms of the Akaike Information Criterion (AIC)[25].

5.1 Univariate Survival Analysis

Table 3 synthesizes the results for the S&P subsample of the univariate Cox models estimated on covariates obtained by combining the risk measure and time lag between the state of the company and the risk indicator. To make the coefficients comparable, we standardized all measures using their respective full sample average and standard deviation.

In most cases, with the exception of the DY-from and the BGLP-in indicators, the estimated coefficients are significant and with the expected sign.

More specifically, at 0 and 1-week lags, the systematic risk measures with the best AIC[26] are VaR_2 and ES_2, while SES_2 clearly dominates among the systemic risk measures.

[24]We estimate the traditional Cox models using the `R` package `survival` (Therneau, 2015), and the Cox-Lasso models with `R` package `penalized` (Goeman *et al.*, 2017). As detailded in Goeman (2010), parameters are optimized using a full gradient algorithm that combines gradient ascent and Newton-Raphson. The algorithm, particularly efficient for CV strategies, can be extended to incorporate ridge penalties, elastic net penalties and non-negative constraints (cf. Footnote 23). In this work we did not try Ridge or Elastic Nets because the main focus is on variable selection and not on prediction accuracy.

[25]The results obtained using GJR-GARCH in place of T-GARCH are available upon request.

[26]The table reports AIC rather than the partial log-likelihood because this index allows a direct comparison of models with different numbers of covariates.

Table 3: **S&P subsample**. Univariate Cox regressions by risk measure and lag between the event and the risk measure. AIC indicates the Akaike Information Criterion (three best values highlighted in bold). ***, **, and * denote significance of the corresponding coefficient at 1%, 5% and 10%, respectively.

	none		1 week		1 month		3 months		6 months	
	coef	AIC	coef	AIC	coef	AIC	coef	AIC	coef	AIC
$Beta_1$	1.498***	72.39	1.348***	78.86	1.362***	79.10	1.093***	78.57	1.062***	93.80
$Beta_2$	0.851***	75.64	1.095***	80.74	1.135***	79.03	0.634***	81.70	0.749***	93.14
VaR_1	-1.152***	86.22	-1.104***	88.65	-1.034***	91.58	-1.047***	94.14	-1.140***	96.10
VaR_2	-1.133***	59.24	-1.226***	76.80	-0.738***	91.35	-0.678***	80.89	-0.829***	91.72
ES_1	-1.212***	72.12	-1.121***	79.49	-1.058***	82.58	-1.031***	86.32	-0.916***	96.42
ES_2	-1.049***	60.42	-1.192***	76.58	-0.657***	91.63	-0.646***	79.97	-0.696***	92.90
MES_1	-1.630***	83.26	-1.399***	90.52	-1.403***	92.00	-1.476***	89.33	-1.562***	96.59
MES_2	-1.377***	71.21	-1.303***	87.14	-0.797***	95.72	-0.544**	86.11	-0.807***	95.50
SES_1	1.201***	**47.81**	1.295***	**59.65**	1.181***	**66.32**	1.651***	**62.27**	1.495***	**80.45**
SES_2	1.019***	**45.88**	1.123***	**61.48**	0.808***	**76.26**	1.235***	**66.73**	1.333***	**80.20**
$SRisk_1$	0.464***	96.75	0.462***	97.09	0.482***	96.81	0.493***	97.14	0.525***	96.46
$SRisk_2$	0.410***	97.05	0.413***	96.89	0.419***	96.91	0.414***	97.54	0.438***	96.78
E-$CoVaR_1$	-1.235***	84.24	-1.185***	87.07	-1.170***	87.73	-1.368***	86.88	-0.969***	98.64
E-$CoVaR_2$	-1.087***	72.84	-1.159***	86.62	-0.701***	94.96	-0.723***	82.21	-0.676***	96.08
DY-from	-0.667**	100.23	-0.725***	99.30	-0.585**	100.67	-0.194	104.54	-0.152	104.63
BGLP-in	0.147	104.48	0.711***	97.27	0.632**	99.17	0.297	103.62	-0.107	104.65
LVG	0.977***	**48.41**	0.919***	**65.07**	0.735***	**73.51**	1.533***	**65.47**	1.484***	**79.90**

Table 4: **Non-S&P subsample**. Univariate Cox regressions by risk measure and lag between the event and the risk measure for Non-S&P companies. AIC indicates the Akaike Information Criterion (three best values highlighted in bold). ***, **, and * denote significance of the corresponding coefficient at 1%, 5% and 10%, respectively.

	none		1 week		1 month		3 months		6 months	
	coef	AIC	coef	AIC	coef	AIC	coef	AIC	coef	AIC
$Beta_1$	0.696***	141.75	0.405*	150.26	0.226	152.17	0.684***	143.75	0.928***	138.87
$Beta_2$	0.451***	147.48	0.437***	147.51	0.132	152.68	0.061	152.93	0.809***	135.07
VaR_1	-1.902***	67.89	-1.792***	74.46	-1.726***	**79.91**	-1.691***	88.98	-1.953***	90.89
VaR_2	-0.941***	**64.21**	-1.216***	**72.92**	-0.994***	104.82	-1.095***	103.85	-1.313***	99.34
ES_1	-1.526***	**53.71**	-1.407***	**67.70**	-1.524***	**77.21**	-1.790***	79.31	-1.660***	**93.32**
ES_2	-0.993***	**62.12**	-1.244***	**69.72**	-0.975***	100.20	-1.114***	100.83	-1.259***	98.07
MES_1	-1.105***	130.94	-0.734***	147.03	-0.669**	148.56	-1.025***	140.01	-1.318***	133.64
MES_2	-1.036***	112.79	-0.746***	133.22	-0.725***	146.90	-0.617***	147.40	-0.845***	132.73
SES_1	0.614***	86.13	0.793***	82.12	0.920***	**77.96**	2.042***	**67.01**	2.023***	**91.39**
SES_2	0.559***	75.43	0.793***	76.83	0.721***	83.12	1.679***	**70.53**	1.837***	**93.75**
$SRisk_1$	1.054***	133.98	1.048***	134.44	1.013***	136.45	0.952***	138.71	0.881***	141.28
$SRisk_2$	1.081***	130.82	1.103***	129.64	1.054***	132.44	0.996***	134.72	0.997***	135.72
E-$CoVaR_1$	-1.872***	81.25	-1.703***	93.80	-1.658***	96.89	-1.527***	102.63	-1.585***	106.31
E-$CoVaR_2$	-1.001***	103.71	-0.611***	132.97	-0.727***	138.94	-0.565***	143.25	-0.630***	129.48
DY-from	-0.861***	134.97	-0.902***	133.16	-0.832***	136.61	-0.944***	132.35	-0.839***	138.10
BGLP-in	1.091***	128.94	1.176***	125.78	0.814***	139.87	0.850***	138.91	0.887***	138.25
LVG	0.549***	76.61	0.778***	78.72	0.701***	82.80	1.712***	**68.78**	1.774***	95.50

Furthermore, the best systemic measure outperforms the best systematic measure. As expected, the model-based measures (index 2) are generally superior to the historical-based versions.

At the 1-month and 3-month lags, the best fitting systematic indicator is Beta, though VaR_2 and ES_2 are quite close, and the best fitting systemic indicators continue to be SES_2 and SES_1.

The 6-month lag confirms to the earlier evidence, with the two SES and the VaR_2/ES_2 the best in the respective subgroups. Again, the best systemic measure perform better than systematic ones.

Table 4 summarizes results for the Non-S&P subsample. The best systematic indicators are clearly the two ES, followed by VaR, while SES outperforms the other systemic measures. These findings are stable across lags. Differently from the S&P group, the best systematic measure is better than the best systemic indicator at all lags, with the exception of 3-month lag. Furthermore, we find that Beta is often not significant.

As highlighted by Figure 1, there is a considerable decline in AIC in moving from 0 toward higher lags, especially up to the 1-month lag.

To summarize, the univariate analysis shows some clear results. First, in above comments we purposely avoided to discuss LVG, which has been included in the analysis only as a control variable. It is however clear from Tables 3 and 4 that the performance of this indicator almost replicates SES_2 at all lags (since SES_2 is a combination of MES_2 and LVG – cf equation (7) – we argue that the former component provides to SES_2 only a marginal improvement over LVG). Supported by their high correlations (cf. Tables 1 and 2), this result leads us to conclude that the information content of such two variables is substantially the same, so that we removed SES_2 from the multivariate analysis.[27]

[27] Results of the multivariate analysis obtained including also SES_2 are however reported in Table 18 of the Appendix. The high correlation between SES (in the two versions) and LVG is due to the extremely long right tail of the distribution of the latter variable. Among S&P companies, the variables ranges between 1.02 and 5283.73 (but the maximum is outlying, considering that the closest value is 477.30) with percentiles $LVG(0.10) = 1.39$, $LVG(0.90) = 19.42$, $LVG(0.99) = 94.32$; for the Non-S&P companies, the range is $(2.18, 2564.31)$, with percentiles $LVG(0.10) = 4.58$, $LVG(0.90) = 21.46$, $LVG(0.99) = 215.73$. Just for reference, the same statistics for MES_2 (taken in percentage and reversing its sign for comparison reasons) are: $MES_2(min) = -1.1$, $MES_2(0.10) = 1.2$, $MES_2(0.90) = 8.9$, $MES_2(0.99) = 20.9$, $MES_2(max) = 91.1$ in the S&P companies; $MES_2(min) = -6.2$, $MES_2(0.10) = 1.3$, $MES_2(0.90) = 6.8$, $MES_2(0.99) = 13.1$, $MES_2(max) = 35.4$ in the Non-S&P companies. The incidence of the long tail

Second, in most cases model-based measures achieve better AIC than historical-based measures. As a consequence, in Section 5.2 we present the multivariate analysis with the model-based indicators, while the results for the historical-based measures are reported in the Appendix.[28]

Finally, BGLP-in and DY-from achieve the worst AIC at all lags in both subsamples. We interpret this result as a consequence of the fact that such indices measure connectedness, rather than risk. There is however some difference between the performances of the two indicators: BGLP-in has usually the expected sign, DY-from has the opposite. This difference may be explained: BGLP-in measures connectedness in returns; DY-from makes something similar referring to volatility. If one interprets volatility as an approximation of risk, it becomes apparent that the second does not measure risk, but connectedness in the levels of risk, which may move together even when risk goes down; however with a relatively poor performance, causality in the standardized returns seems instead to preserve some ability in capturing propagation of risk. Because of this poor performance, we remove DY-from from the multivariate analysis of the next sessions.

5.2 Multivariate Survival Analysis with Penalty

This section discusses the results of the Cox-Lasso models. As detailed in Section 4.3, the penalty parameter is selected by k-fold CV with $k = 20$. Since the results of this strategy change as a consequence of the (random) allocation of the observations in the k groups, we estimated each model three times using different (random) groupings: the outcomes, within each lag, are reported in Tables 5 and 6 as separated columns.

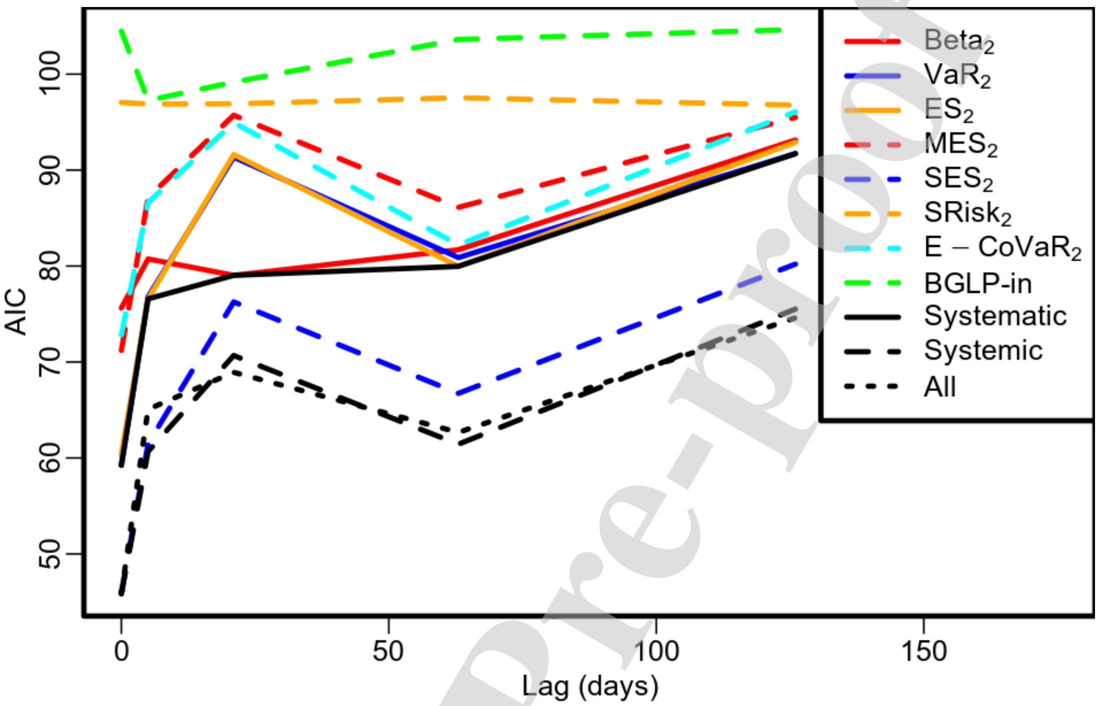
Table 5 reports the outcomes for the systematic risk measures. In the S&P subsample, ES_2 is selected at all time horizons with the exception of the 1-month lag; Beta_2 is selected at 1-week, 1-month and 6-month lags; VaR_2 is included at lag 0 and 6-month.

distribution of LVG is also proved, indirectly, by the difference between the Pearson and Spearman (LVG, SES)-correlations, with the latter on lower levels (cf. Tables 1 and 2; considering how survival models are estimated, we notice as they tend to be more affected by Pearson than by Spearman correlations). To summarize these considerations, from a statistical point of view LVG plays a dominant role over MES in determining SES, especially among Non-S&P companies.

[28]Because of the discussion reported in footnote 27, we removed SES_1 from the historical-based measures.

Figure 1: Pattern of AIC values, by lag, reported in the univariate (colored lines) and post-Lasso (black lines) Cox regressions. In the S&P plot, the lines representing VaR_2 and ES_2 are highly overlapped; in the Non-S&P plot, the lines representing ES_2 and Systematic are entirely overlapped.

(a) S&P Companies.



(b) Non-S&P Companies.

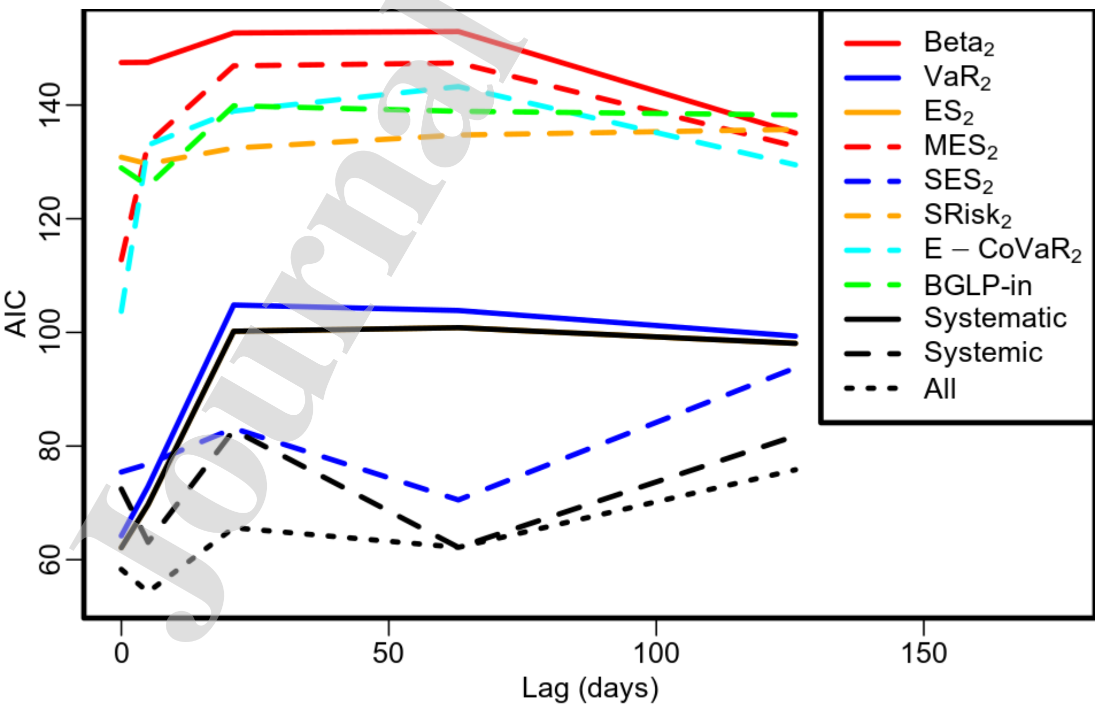


Table 5: Coefficient estimates of the multivariate Cox-Lasso model for the systematic risk measures by lag and group (S&P and Non-S&P companies) between the company state and risk indicator; blank space indicates that the risk measure is not selected by the Cox-Lasso. For each lag (in column), the three sub-columns correspond to different allocations of the observations in the k groups of the k-fold CV.

		none			1 week			1 month			3 months			6 months		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
S&P	$Beta_2$				0.176	0.176	0.359	1.054	1.057	1.068				0.162	0.153	0.138
	VaR_2	-0.436	-0.267	-1.068										-0.042	-0.199	-0.451
	ES_2	-0.420	-0.537	-0.022	-0.711	-0.711	-0.953				-0.312	-0.308	-0.293	-0.359	-0.240	-0.048
Non-S&P	$Beta_2$															
	VaR_2															
	ES_2	-0.892	-0.903	-0.900	-1.075	-1.069	-1.071	-0.813	-0.754	-0.855	-0.829	-0.779	-0.825	-0.984	-0.851	-0.755

Interestingly, VaR_2 and $Beta_2$ provide additional information over ES_2 at 6-month lag. Summarizing, all the considered risk measures seems to play a role in anticipating the state of the companies, and no clear winner emerges among them. In the Non-S&P subsample, the outcome is strikingly different: only ES_2 is selected at all lags, while VaR_2 and $Beta_2$ never appear.

Table 6 summarizes the results of a similar analysis for the systemic risk measures.[29] In the S&P subsample, LVG always appears while E-$CoVaR_2$ and BGLP-in seem to play no role. MES_2 and $SRisk_2$ have some effect at the longest horizons. Thus, at 6-month lag, a combination of MES_2 and $SRisk_2$ together with the LVG is the best fitting mix. In the Non-S&P subsample, it is confirmed that LVG is always selected and that MES_2 has non zero coefficients at none, 1-week and 6-month lags.

Although systematic and systemic risk measures play partially different roles, for sake of completeness, we apply the Cox-Lasso also including all indicators. In the S&P subsample (Table 7), results are similar to those found for systemic indicators alone: LVG is always selected while E-$CoVaR_2$ and BGLP-in are never included. At 6 months, only $Beta_2$ seems to provide additional information over $SRisk_2$ and LVG. Instead, in the Non-S&P subsample (Table 7) the results are quite clear: LVG and ES_2 are selected at all lags and thus seem to dominate over the others.

[29] We included LVG among the systemic indicators because it is used in calculating and SRisk and the two SES measures that we removed from the analysis.

Table 6: Coefficient estimates of the multivariate Cox-Lasso model for the systemic risk measures by lag and group (S&P and Non-S&P companies) between the company state and risk indicator; blank space indicates that the risk measure is not selected by the Cox-Lasso. For each lag (in column), the three sub-columns correspond to different allocations of the observations in the k groups of the k-fold CV.

		none			1 week			1 month			3 months			6 months		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
S&P	MES_2										-0.137	-0.137	-0.136	-0.166	-0.297	-0.290
	$SRisk_2$					0.155		0.380	0.403	0.406				0.421	0.561	0.552
	$E\text{-}CoVaR_2$															
	BGLP-in															
	LVG	0.599	0.591	0.591	0.398	0.605	0.398	1.413	1.413	1.413	0.444	0.442	0.561	0.563	0.541	0.601
Non-S&P	MES_2	-0.160	-0.100	-0.121	-0.229	-0.226	-0.276							-0.370	-0.353	-0.403
	$SRisk_2$						1.005					0.113	0.108			0.762
	$E\text{-}CoVaR_2$															
	BGLP-in						0.077	0.045	0.598							
	LVG	0.650	0.646	0.362	0.340	0.347	0.457	0.457	0.429	0.549	1.05	1.077	0.535	0.532	1.077	0.468

Table 7: Coefficient estimates of the multivariate Cox-Lasso model for both the systematic and systemic risk measures by lag and group (S&P and Non-S&P companies) between the company state and risk indicator; blank space indicates that the risk measure is not selected by the Cox-Lasso. For each lag (in column), the three sub-columns correspond to different allocations of the observations in the k groups of the k-fold CV.

		none			1 week			1 month			3 months			6 months		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
S&P	$Beta_2$	0.071						0.174		0.292	0.059	0.040	0.012	0.190	0.003	0.197
	VaR_2													-0.054		-0.172
	ES_2	-0.293		-0.072												
	MES_2										-0.094	-0.108	-0.128			
	$SRisk_2$	0.313						0.321		0.416				0.409	0.254	0.503
	$E\text{-}CoVaR_2$															
	BGLP-in															
	LVG	0.605	0.575	0.576	0.398	0.479	0.409	0.395	0.423	0.390	0.580	0.568	0.551	0.615	0.566	0.646
Non-S&P	$Beta_2$															
	VaR_2															
	ES_2	-0.334	-0.369	-0.364	-0.490	-0.402	-0.569	-0.472	-0.478	-0.518	-0.087	-0.087	-0.095	-0.664	-0.659	-0.700
	MES_2															
	$SRisk_2$						0.741	0.620	0.745	0.860			0.019			0.071
	$E\text{-}CoVaR_2$						0.077			0.095						
	BGLP-in				0.159		0.618									
	LVG	0.226	0.231	0.231	0.332	0.343	0.322	0.421	0.421	0.420	1.008	1.008	1.011	0.295	0.295	0.297

5.3 Multivariate Survival Analysis with Selected Risk Measures

To check the results of the multivariate Cox-Lasso analysis and, possibly, to obtain even stronger conclusions, we run traditional multivariate Cox regressions starting from the outcome of the Cox-Lasso models. More specifically, we include all risk measures selected at least once by Cox-Lasso as covariates in the three k-fold CV repetitions (see Section 5.2 and tables therein). Then, if at least one estimated coefficient results not significant (at 5%, undirectional alternative) or has the "wrong" sign, we repeat the regression removing the least significant among those having the characteristics indicated.[30] We stop when all coefficients are significant and with the expected sign.

Tables 8 and 9 report the results for the S&P and Non-S&P companies, respectively. For the systematic risk measures we obtain mixed evidence among the different lags in the S&P subsample whereas in the Non-S&P subsample, ES_2 clearly dominates at all horizons (a trivial outcome considering Table 5).

For the systemic risk measures, the Cox-Lasso analysis confirms the previous findings. In particular, in both the S&P and Non-S&P subsamples, LVG and SRisk_2 have a major role in anticipating the state of the companies: LVG is selected at all time horizons while SRisk_2 is included at the 1-week, 1-month and 6-month lags.

Finally, the direct comparison between the two groups of risk measures reveals a prevalence of systemic indicators (SRisk_2 and LVG) over the systematic ones for S&P companies, whereas in the Non-S&P subsample, ES_2 still provides additional information, over the systemic measures, at almost all lags.

It is important to remark that, as expected, the post-Lasso analysis provides a cleaner picture of the results. In addition to remove negligible coefficients, the availability of comparable fit statistics, the AIC in particular, suggests further considerations. For the S&P companies, the multivariate analysis suggests that it is not possible to combine different systematic measures in order to improve the AIC over the univariate case. By the contrary, for the systemic measures the improvement from using many indicators is relevant. For instance, at 6-month lag, adding SRisk_2 to LVG improves the AIC over LVG alone by 5.6 points (see also Figure 1 panel (a)). Moreover, the AIC of the systemic models are better (i.e. lower) than those of systematic models at all lags and the difference is quite large. The worsening in the AIC of the systematic measures is faster than that of systemic measures. Related to this, we note that adding systematic measures to the

[30] Cf Footnote 23 for a discussion on the coefficient associated to a risk indicator when no sign restrictions are employed.

systemic ones (panel 'All' vs 'Systemic') provides a small improvement at the 1-week lag, 3-month lag and 6-month lag. Overall, when used together, the systemic indicators give some complementary information that improves the model fit over the univariate use. This indicates that systemic risk cannot be incorporated in a unique accepted measure, so that a combination of risk measures is more adequate to capture this multi-faceted concept. Adding the systematic measures to the systemic ones (panel 'All' vs 'Systemic' and panel 'All' vs 'Systematic') generates only a slightly better model fit over systemic models alone, at 3-month and 6-month lags (see also Figure 1 panel (a), label 'All'). For example, at 6-month lag a combination of SRisk_2, VaR_2 and LVG improves the AIC over the best combination of systemic measures by 1 point.

Differently, in the Non-S&P subsample, the combination of many systemic measures generates a tangible improvement of the AIC at all lags, with exception of 1-month. For instance, at 6-month lag, adding MES_2 and SRisk_2 to the LVG improves the AIC over LVG alone by 13 points. Although the AIC of the systematic model is lower than in the systemic model at lag 0, at longer lags, the relationship reverses and the difference is quite large, meaning that systemic measures tend to outperform systematic measures especially at longer horizons. Another difference with the S&P subsample, emerges regarding the importance of ES_2. In fact, adding it to the systemic indicators (panel 'All' vs 'Systemic' and panel 'All' vs 'Systematic') gives a substantially lower AIC, over both systematic and systemic models alone, at almost all lags (see also Figure 1 panel (b), label 'All'). For example, at 6-month lag a combination of SRisk_2, ES_2 and LVG improves the AIC over the best univariate indicator by 13 points and by 4.6 points if we consider the best combination of systemic measures. To summarize, the role of systematic measures, especially ES_2, seems to be more relevant in the Non-S&P than in the S&P companies.

6 Conclusions

This study compares the empirical performance of several systemic and systematic risk measures. The ground for such comparison is the distress of financial institutions, the most catastrophic and tangible expression of financial risk. Using data for 171 listed

Table 8: **S&P subsample**. Results of the multivariate Cox regressions on the risk measures selected by the Cox-Lasso, refined using an iterative selection procedure that excludes insignificant variables (at 5%, unidirectional alternative) or those with a coefficient having a sign different from the a priori expectation (details at the beginning of Section 5.3). The table presents three panels for the different sets of risk measures and, within each, for the different lags. t-statistics in parentheses.

	Systematic					Systemic					All				
	none	1 week	1 month	3 months	6 months	none	1 week	1 month	3 months	6 months	none	1 week	1 month	3 months	6 months
$Beta_2$			1.172								0.441			0.288	
			(4.859)								(1.718)			(2.107)	
VaR_2	-1.208				-0.847										-0.505
	(-5.250)				(-4.086)										(-1.839)
ES_2		-1.267		-0.668											
		(-5.351)		(-3.287)											
MES_2									-0.205						
									(-1.876)						
$SRisk_2$							0.507	0.662		0.634			0.662		0.672
							(2.605)	(3.358)		(3.197)			(3.358)		(3.221)
$E\text{-}CoVaR_2$															
BGLP-in															
LVG						1.069	0.650	0.526	1.065	0.891	0.865	0.723	0.526	1.045	0.716
						(4.481)	(3.520)	(4.398)	(3.642)	(4.099)	(4.429)	(4.150)	(4.398)	(3.571)	(3.104)
AIC	59.24	76.58	79.03	79.97	91.72	48.41	61.87	67.18	63.06	74.34	47.09	65.07	67.18	61.87	73.36

Table 9: **Non-S&P subsample**. Results of the multivariate Cox regressions on the risk measures selected by the Cox-Lasso, refined using an iterative selection procedure that excludes insignificant variables (at 5%, unidirectional alternative) or those with a coefficient having a sign different from the a priori expectation (details at the beginning of Section 5.3). The table presents three panels for the different sets of risk measures and, within each, for the different lags. t-statistics in parentheses.

	Systematic					Systemic					All				
	none	1 week	1 month	3 months	6 months	none	1 week	1 month	3 months	6 months	none	1 week	1 month	3 months	6 months
$Beta_2$															
VaR_2															
ES_2	-1.059	-1.297	-0.982	-1.090	-1.152						-0.683	-0.600	-0.559		-0.817
	(-6.081)	(-6.714)	(-6.803)	(-6.512)	(-5.930)						(-3.064)	(-2.916)	(-2.607)		(-2.975)
MES_2						-0.324				-0.471					
						(-1.709)				(-2.023)					
$SRisk_2$							1.536		1.271	1.135		1.304	1.416	1.271	1.118
							(3.897)		(3.056)	(2.953)		(2.167)	(3.434)	(3.056)	(2.789)
$E\text{-}CoVaR_2$															
BGLP-in												0.752			
												(2.718)			
LVG						0.390	0.648	0.692	1.216	0.552	0.212	0.346	0.443	1.216	0.369
						(3.148)	(4.656)	(6.857)	(5.769)	(3.258)	(1.905)	(2.932)	(4.084)	(5.769)	(1.968)
AIC	62.12	69.72	100.20	100.83	98.07	73.91	66.03	82.80	62.04	82.76	58.30	52.87	63.67	62.04	78.11

US financial companies (29 distressed) during 2006-2010, we estimate *historical-based* and *model-based* versions of three systematic and six systemic risk measures along with leverage as a control variable and we correlate the state (distressed or not) of the company at a given time to the risk measures estimated at the same time, one week, one month, three months, and six months before. On the two subsamples of S&P and Non-S&P companies, we perform two different analyses: separate univariate Cox regressions for each risk measure to select, on a stand-alone basis, the one with the highest predictive power for the state of the company; multivariate Cox regressions to check whether, within the two groups of risk indicators, there is one condensing all predictive information about the distress or whether they can be used jointly to enhance the global predictive ability.

On a stand-alone basis, each risk measure emerges as a significant predictor, and with the expected sign, of the company distress at all horizons, with the exception of DY-from in both subsamples, and BGLP-in in the S&P subsample only. As expected, the predictive information of the risk measures tends to worsen with time but this happens differently in the two groups, in the sense that the systemic measures are always better than the systematic ones, except at very short lags in the Non-S&P subsample.

The multivariate analysis evidences the important role of LVG, in the sense that it is selected in both subsamples at all lags. Despite this, SRisk_2 provides additional information about the state of the company in both subsamples. At the longest horizon, a combination of VaR_2, SRisk_2 and LVG improves the model fit substantially over the best stand-alone measure for S&P companies, while a combination of ES_2, SRisk_2 and LVG provides the best performing mix for Non-S&P companies. Differently from Benoit *et al.* (2013, 2017), who assert that systemic indicators are driven by market risk measures and firm characteristics, our findings seem to suggest that systemic risk measures still have an additional information content over systematic risk measures and leverage.

Our findings have implications for both regulators and supervisors. Within both systemic and systematic measures, some indicators outperform in modeling financial companies' distress. We believe that supervisors should concentrate their efforts on such measures. Moreover, we propose a multivariate model based on a combination of risk measures with a better fit than using the indicators one by one. This may also help a more effective identification of systemic important financial institutions. Compared to previous studies, this approach provides a different way to validate a given set of risk measures. Supervisors and regulators may apply it on a daily basis to check whether and how much the hazard rate of each company tends to worsen.

Our research can be extended in several directions. Using the same methodology, we could compare global systemic risk measures with source-specific systemic risk measures (e.g., LMI, ACRISK). This could highlight whether the global ones are sufficient to predict distress scenarios, or, in contrast, they are too condensed to properly capture the multi-faceted nature of systemic risk, so that the latter can usefully complement them. Researchers can also apply the methodology to different ways to estimate the risk measures considered here. It would be also interesting to analyze data for companies outside the US to check whether the results are robust from a geographical point of view.

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Highlights

- We perform an empirical validation of systemic and systematic risk measures
- We use univariate and multivariate Cox regressions combined with Lasso penalty
- Systemic indicators and leverage reveal strong prevalence over systematic measures
- A combination of VaR, SRisk and Leverage is the best mix for S&P companies
- A combination of ES, SRisk and Leverage provides the best mix for Non-S&P companies

The Beauty Contest between Systemic and Systematic Risk Measures: Assessing the Empirical Performance

Fabrizio Cipollini
DiSIA, University of Florence, Italy
e-mail: fabrizio.cipollini@unifi.it

Alessandro Giannozzi
DiSEI, University of Florence, Italy
e-mail: alessandro.giannozzi@unifi.it

Fiammetta Menchetti
DiSIA, University of Florence, Italy
e-mail: fiammetta.menchetti@unifi.it

Oliviero Roggi*
DiSEI, University of Florence, Italy and Fundação Dom Cabral, Brazil
e-mail: oliviero.roggi@unifi.it

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Abstract

To assess the empirical performance of systemic and systematic risk measures and to face some legitimate concerns in literature regarding the connections between those indicators, we investigate how the state (distressed or not) of a financial company at a given date is related to the corresponding risk indicators. Based on a combination of univariate and multivariate Cox regressions, our approach is applied

*Corresponding author: Dipartimento di Scienze per l'Economia e l'Impresa (DiSEI), Università di Firenze, Via delle Pandette, 9 - 50127 Firenze, Italy; ph. +39 055 2759 720.

to 2006-2010 data of 171 listed US financial companies (grouped in two subsamples, S&P and Non-S&P), on which we estimate different versions of nine popular systematic and systemic risk measures, along with leverage as control variable.

Results reveal a strong prevalence of systemic measures and leverage over systematic ones, especially when the time distance between the indicator and the event tends to increase. For the S&P companies, a combination of SRisk and leverage provides a considerable improvement over the best stand-alone indicators, while Expected Shortfall emerges as the only systematic measure providing some information in addition to SRisk and leverage for Non-S&P companies.

Keywords: Systemic and Systematic risk, Cox model, Lasso penalization

JEL codes: G01, G21

Alessandro Giannozzi: conceptualization; Data curation, Writing-original draft; Methodology. Fabrizio Cipollini: Formal analysis; Methodology; Writing-orginal draft. Fiammetta Menchetti: conceptualization; Data curation, Writing-original draft; Methodology. Oliviero Roggi: conceptualization; Writing-original draft; supervision.