Systemic risk measures and EBA stress tests

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Abstract

Regulators' stress tests on banks, further stimulated an academic debate over systemic risk measures and their predictive content. Focusing on marked based measures, Acharya et al. (2010) provides a theoretical background to use Marginal Expected Shortfall (MES) for predicting the stress test results, and verify it on the 2009 Supervisory Capital Assessment Program of the US banking system. The aim of this paper is to further test the goodness of MES as a predictive measure, by analysing it in relation to the results of the European stress tests exercise conducted by The European Banking Authority. As for the 2014 stress test exercise, our results underscore the importance of choosing the appropriate index to capture the systemic distress event. In fact MES based on a global market index does not show association with the stress test, in contrast to F-MES, which is based on a financial market index, and has a significant information and predictive power. By moving to analyse the most recent 2016 EBA stress test, we find slightly different results.

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1. Introduction

The recent financial crisis highlighted the importance of interconnections in the financial system and the need to measure the impact of contagion. Following the crisis a rich literature has been growing on the very same problem of defining systemic risk and the issues connected to its measurement. Despite these efforts, there is still no consensus either on the very same definition of systemic risk, or on a single risk measure. For example, in ECB (2009, p. 134) systemic risk is defined as «risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially». Benoit et al. (2015, p.4) refers to the «risk that many market participants are simultaneously affected by severe losses, which then spread through the system». While different definitions can be found in the literature stressing different aspects, generally speaking systemic risk involves the whole financial system instead of the single institution and it spreads over the real economy. However, the existence of multiple definitions of systemic risk has naturally implied the development of a wide range of measures for gauging it.

Systemic risk by its nature involves both a cross-sectional and a time dimension, and available measures captures these two dimensions in different ways. Given the huge variety of measures, a classification of them is a difficult task, but excellent surveys and different classifications are offered in Bisias et al. (2012), De Bandt et al. (2013) and Benoit et al. (2015). Far from being exhaustive, we recall the most common measures in order to frame our analysis. First, we can differentiate between measures based on the single bank, which essentially modify traditional risk measures so as to include contagion effects, and measures based on the system as a whole. As for the first group, the metrics can be based on market data (mainly equity returns or CDS spread) or on balance-sheet and regulatory data. The second group instead includes on the one hand measures of connectivity based on networks (graph theory) which focus on the cross-sectional dimension of risk only, on the other hand it considers early warnings indicators which captures the time dimension. Benoit et al (2015) distinguish between global statistical measures based on market prices and measures based on a "source-specific approach", where generally an underlying economic model drives the choice of the risk sources. As for the first group, the main risk measures are CoVaR introduced by Adrian and Brunnermeier (2011) and Marginal Expected Shortfall (MES) proposed by Acharya et al. (2010). These measures have the advantage of relying on market data which are publicly available in real time. Benoit et al. (2015) stress that an integration between the two approaches is desirable and Lee et al. (2013, p. 759) underscore that "*the use of MES, a top-down measure, and CoVaR, a bottom-up measure, allows the systemic risk to be measured from different angles*".

Focusing on the market-based risk measures[3], CoVar, MES and their modifications have been lately applied to banks in different countries (mainly US and European) to evaluate their capability of measuring systemic risk. For example, Girardi and Ergun (2013) propose a modification of CoVaR using multivariate GARCH and apply this methodology to US financial institutions. Banulescu and Dumitrescu (2015) propose the Component Expected Shortfall, that is a modification of MES which accounts for the size (market capitalization). Lee et al. (2013) measure the contributions of Korean banks to systemic risk based on both CoVaR and MES. Acharya et al. (2012) develop a measure based on MES, called SRISK, which has become a standard[4] for systemic risk. SRISK measures the expected capital shortfall of a firm in a crisis: the risk measure used is a long run marginal expected shortfall and the crisis is identified by a 40% drop in a global equity index over six months[5].

The recent crisis has shown the importance of controlling for systemic risk in order to preserve financial and macroeconomic stability and, in the end, to guarantee economic growth and welfare. As a natural consequence, this issue has been of interest not only for the academia but also for regulators, which have been working hard in order to improve the architecture of financial supervision. Focusing on Europe, among the new authorities the European Banking Authority (EBA) has a particularly important role in preserving the solvability of the banking system. Starting from 2011 EBA have been conducting stress test exercises on the European banking system, testing its resilience to adverse macroeconomic scenarios in terms of single banks' capital over risk weighted assets ratio. The stress test over a single bank is based on the bank's balance sheet and on a scenario generated by stressing several financial and economic variables. Despite the efforts, current stress tests do not fully satisfy their purpose: as Borio et al. (2014) highlight, "given current (modelling) technology, macro stress tests are ill-suited as early warning devices", even if they can be more reliable as crisis management tools. Moreover the Financial Stability Board (FBS) and the Basel Committee on Banking Supervision (BCBS) publish annually a list of the most systemically important banks (G-SIBs)[6]: the classification is based on the calculation of a score dependent on banks' features (see BCBS (2014) for a description of the methodology adopted) and it is used to set additional capital requirements for riskiest banks.

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[3]In this work we focus on MES and CoVaR, but other market-based measures of systemic risk have been recently developed: for example, Black et al.(2016) calculate the Distress Insurance Premium (DIP) for European banks.
[4] NYU Stern School of Business provides a daily updated estimation of SRISK for US financial institutions (http://vlab.stern.nyu.edu/welcome/risk)
[5] The associated econometric model is developed in Brownless and Engle (2011).
[6] Bongini et al. (2015) developed an event study on the impact of the publication of the list of systemically important banks on market prices.

Based on the strong connection between the actions undertaken by the regulators and the developments of the academic literature on systemic risk measures, Acharya et al. (2010) compare the results from the US SCAP 2009 to the systemic risk estimates they obtain based on Marginal Expected Shortfall (MES) and find that MES is a good predictor for the outcome of the stress test. This result is very interesting since regulatory stress tests are based on private information (banks' individual exposures) while MES relies on publicly available market data only. However, similar comparison for European countries does not provide the same outcome. Based on the 2011 U.S. and European stress tests, Acharya et al. (2014) compare capital shortfalls measured by the regulator to those based on SRISK and they find a significant divergence for Europe . In particular, SRISK produces much higher overall capital shortfall and single bank results uncorrelated to the EBA ones. They show that the difference can be imputed to the fact that risk measures used in risk-weighted assets (i.e. in regulatory stress tests) are cross-sectionally uncorrelated with market measures of risk. Acharya and Steffen (2014a) found similar results in relation to the 2014 stress test for the eurozone banks using aggregate data by countries. Moreover, based on the same data Acharya and Steffen (2014b) show that the inconsistencies between the EBA stress tests results and the SRISK estimates are due to the capital ratio used by EBA: by considering simpler ratios (not based on risk weights) a positive correlation between EBA results and SRISK emerges[7].

Overall, as stressed by Engle et al. (2015), measuring systemic risk for European countries is a more demanding task compared to US, since crises in Europe may stem from very different sources, and to accounted for this different indexes have to be used.

Against this backdrop, the aim of this paper is to contribute to this literature by providing further evidence on the informative/predictive content of market based risk measures for European banks with respect to regulatory stress test, and specifically to verify the sensitivity of the results to the reference index used. To this end we first analyse the relation between the October 2014 EBA stress test of the European banking system and MES, based on different reference indexes, including a financial one (F-MES). Secondly, we move to analyse the recent 2016 EBA stress tests for comparison.

[7] As suggested in Acharya et al. (2012), market-based measures of systemic risk could also be used to set minimum capital requirements. However, some authors show some scepticism on the use of these measures by regulators. For example, Daniellson et al. (2015), based on a model of regulator's optimal policy choice, show that a systemic risk measure in order to be useful for regulators should have a degree of reliability far higher than currently available measures such as CoVaR and MES.

The paper is structured as follows. In Section 2 we review the main bank-level measures of systemic risk based on market data, focusing on the Marginal Expected Shortfall (MES) proposed by Acharya et al (2010). In Section 3 we illustrate the dataset, we present our analyses and we discuss the results. Last Section concludes.

2. Systemic risk measures based on stock market data

The literature on systemic risk has been growing very fast in the last decade and, as stressed in the Introduction, a great variety of measures for systemic risk are now available. Focusing on bank-level measures based on stock market data, the most common metrics for systemic risk are CoVaR and MES. These measures stem from an extension of traditional risk measures, namely Value at Risk (VaR) and Expected Shortfall (ES), which accounts for contagion effects between the single bank and the whole financial system.

Let R_i and R_j be the portfolio returns[8] of two generic institution and q the confidence level, $CoVaR_q^{j|i}$ is implicitly defined as

$$Prob\left(R_j \leq CoVaR_q^{j|i} | R_i = VaR_q^i\right) = q \tag{1}$$

Hence $CoVaR_q^{j|i}$ represents the q quantile of the bank i's return distribution conditional on the event that bank j's return are at the q VaR level. By considering the difference between this measure and the same conditional on the event that bank j's return are at the median level quantifies the contribution of bank i to the risk of bank j. This measure can serve different purposes by changing the interpretation of i and j: if j is interpreted as the whole banking system, then $CoVaR_q^{j|i}$ quantifies the contribution of bank i to the risk of the financial system. On the other hand, if i is interpreted as the banking system, then $CoVaR_q^{j|i}$ quantifies the fragility of bank i in case of a financial crisis.

In order to introduce MES, recall that while VaR represents the maximum loss at a certain confidence level, ES represents average returns in case of exceeding the VaR limit. To define MES, the returns of the whole system are considered: the MES_q^j is defined as the average returns of bank j when the system exceeds its VaR_q level. By interpreting i as the financial system:

[8] VaR and ES are defined here in percentage terms (returns) instead of levels of profit and loss .

$$MES_q^j = E\left(R_j | R_i \leq VaR_q^i\right) \quad (2)$$

This measure is close to the second interpretation of CoVaR, i.e. it quantifies the fragility of bank *i* in case of a crisis. Therefore these two measures are similar in spirit, particularly if compared to other measures of systemic risk. The comparison of VaR and ES can be extended to CoVaR and MES.

As for the estimation, Adrian and Brunnermeier (2011) suggest to estimate CoVaR by quantile regression, while Acharya et al. (2010) estimate MES by historical simulation on *n* observations as:

$$MES_q^j = \frac{1}{nq} \sum_{k=1}^{nq} R_{j,k} \quad (3)$$

where the *nq* observations are selected as the *q* worst realizations of the system returns.

In Section 3, following the lines of Acharya et al. (2010), we focus on MES, which lends itself to be confronted with regulatory stress test exercises, since it captures the fragility of a single bank in the presence of a crisis.

3. Empirical analysis: MES and the EBA 2014 stress test

The EBA stress test exercise aims at quantifying the banks' capital shortfall in a potential future crisis defined by an adverse economic scenario. Acharya et al. (2010) provides a theoretical background to justify the use of MES for predicting the results of a stress test. The authors propose an economic model where the regulator maximises a welfare function capturing the bank owners' utility, the cost of debt insurance and the externality of a financial crisis. The optimal policy emerging from the model consists of a tax also related to the bank's contribution to overall systemic risk, which is quantified by the bank's loss during a crisis (the authors call it *Systemic Expected Shortfall,* henceforth SES). Acharya et. al (2010) formally draw the relation between SES and each bank's MES, i.e. its contribution to the risk (expected shortfall) of the entire system. The model proposed by Acharya et al. (2010) also includes ex-ante leverage as the other component determining SES.

Based on these arguments we analyse the informative content of MES in relation to the results of the 2014 European stress tests exercise. Our empirical analysis is in line with the analysis performed in Acharya et al. (2010) for 2009 US data; we also performed a robustness check over the index used to capture the benchmark portfolio, whereby beside a global market index (used for MES) we consider a financial market index (which defines what we address as F-MES).

3.1. The data

In building our sample we start from the 130 European banks considered in the last EBA's stress test exercise. The stress tests consider the balance-sheet data at the end of 2013 and apply adverse economic scenarios for the period 2014-2016 based on a large number of financial and macroeconomic variables[9]. In particular, banks are evaluated in relation to their *Common Equity Tier 1* both on a baseline and on an adverse scenario: the capital ratio should remain over 8% in the baseline scenario and should not go below 5.5% in the adverse one. From the results published by EBA we infer the following variables to be used in this work:

- *Deficit* is the possible capital shortfall in the adverse scenario, which is zero if capital is above the required level;
- *Total loss* is the cumulative loss on both banking and trading book at the end of 2016 in the adverse scenario.

In order to investigate the relation between the results of the stress tests and the MES as a market data based measure of systemic risk, we need to restrict our sample to the banks quoted on the market. In particular, we want to evaluate the informative content of MES as for its predictive power for the stress test results: therefore we measure MES using daily equity returns over 2013 and use it as 'predictor' over the stress period 2014-2016. By filtering for the availability of equity returns over 2013, we restrict our sample to 53 of the 130 banks. Then we further exclude from the sample 9 banks for which there were not regular exchanges[10] during 2013. As a result we have a sample of 44 banks. Appendix A reports the list of banks in our sample, as well as information about country, capital shortfall, common equity and total loss.

We estimate MES at 5%, that is we take the 5% worst days for the market returns over 2013 and then compute the average equity returns for these days on every bank in the sample. As for the benchmark market portfolio to calculate MES, we consider two alternatives:

[9] See www.eba.europa.eu for details on scenarios.

[10] We excluded banks for which daily returns are zero for more than 25% of the dates considered, which resulted in excluding from the sample the following banks: Alpha Bank, Bank of Cyprus, Bank of Valletta, Dexia NV, Hellenic Bank, Lloyd Banking Group plc, Nova Kreditna Banka Maribor, OsterreichischeVolksbanken AG, Permanent tsb.

- the MSCI Europe as a global economic index thus obtaining standard MES
- the MSCI Europe Banks as an index of the financial sector thus obtaining what is named F-MES.

3.2. The regression analyses for MES and F-MES

The main question we want to answer in this work is: does MES or F-MES predict the results from the stress tests? To this end we use regression analyses and we evaluate the informative content of these measures with respect to two outcomes from the stress tests: the capital shortfall and the total loss. The definition of the variables used in the regression analysis is reported in Appendix B.

As for the capital shortfall, in order to distinguish between banks with zero shortfall (passing the test) and banks with positive shortfall, we create a binary variable (DEF) taking value 1 when there is a capital shortfall. As for total loss, in order to avoid a size effect in the presence of a quite diversified banks' sample, we consider both the ratio of total loss over total assets (LOSS_RATE) and the ratio of total loss over capital (LOSS_CAP). Total assets and capital are observed at the end of 2013 (starting point for our analysis).

Table 1 presents the descriptive statistics for the relevant variables (both observed and estimated) and contains also the variable ES (expected shortfall estimated for the single banks), which will be used later in the analysis, and the variable LEVERAGE (Total assets over book value of equity at 31/12/2013), which is included in the analysis for comparison with Acharya et al. (2010). It can be observed that, as expected, for all the possible variables, the mean conditional on the presence of capital shortfall is higher than the unconditional mean.

Table 1 Descriptive statistics

	DEF	LOSS_RATE	LOSS_CAP	MES	F_MES	ES	LEVERAGE
Mean	0.227273	0.033907	0.695590	2.380455	3.090000	5.853662	16.64065
Median	0.000000	0.032054	0.537085	2.400000	3.105000	4.698641	16.66362
Maximum	1.000000	0.102567	2.321826	5.040000	5.980000	29.13606	36.27221
Minimum	0.000000	0.007184	0.052578	0.580000	0.250000	2.350680	1.893708
Std. Dev.	0.423915	0.020221	0.479518	0.792899	1.387529	4.623816	8.642391
Mean DEF=1		0.054094	1.329262	2.72	4.44	10.3374	20.3635

Data sources: Datasteram and EBA.
Note: 44 observations,"Mean given DEF" is mean conditional on the presence of capital shortfall (DEF=1).

We first consider the binary variable DEF as dependent variable and run a logit regression.[11] Table 2 reports results for the case where each risk measure is considered alone (MES, F-MES, and Leverage in column (1), (2), and (3) respectively) and for the case where MES and F-MES are evaluated jointly with Leverage (column (4) and (5) respectively).

Table 2 The informative content of MES over Capital shortfall: logit regression

Dependent variable: DEF					
	(1)	(2)	(3)	(4)	(5)
Const	-3.0862*** (1.197)	-6.0461*** (1.443)	-2.4839*** (0.8383)	-3.9372*** (1.243)	-8.1032*** (2.4649)
MES	0.7475* (0.4238)			0.6379 (0.4533)	
F_MES		1.3365*** (0.3569)			1.4577*** (0.4275)
Leverage			0.0701* (0.0404)	0.0621 (0.0472)	0.0804 (0.069)
Mean dep. Var.	0.2273	0.2273	0.2273	0.2273	0.2273
McFadden R-squared	0.0518	0.3146	0.0537	0.0885	0.3499

Notes: 44 Observations; Huber-White standard errors; z-statistics in parenthesis; *,**,*** stand for 10%, 5%, 1% significance respectively

As highlighted in Table 2, all risk measures have the correct sign: a higher value increases the probability of having a capital shortfall. Nonetheless, F_MES is much more significant and produces quite a high R-squared value than MES and Leverage. Moreover, when considered jointly, only F-MES keeps a high positive correlation with capital shortfall.

Then we turn to the dimension of losses, and we report results in Table 3 and 4 for the Loss rate and the Loss over capital respectively. Since the introduction of Leverage in the previous regression does not substantially change the picture, here we focus on the informative content of MES and F-MES.[12] As for the Loss rate, the F-MES is again highly significant with a positive sign as expected, while MES is not significant and even has the wrong sign. As for the Loss over capital, the F-MES is again highly significant with positive sign while MES is not significant although but with the expected sign.

In sum, our results are not in favour of the use of MES as predictor for stress test results, and this conclusion is in line with the results found in Acharya and Steffen (2014a) comparing SRISK and the

[11] For a robustness check we also performed a probit regression obtaining the same results.
[12] Further we believe that using Leverage as an explanatory variable is not appropriate when the dependent is the loss rate given it is defined over total asset.

results of the 2014 EBA stress test[13]. The results are more comforting when using F-MES: in fact, when the same measure is calculated with reference to the financial sector instead of the whole economic system it is much more informative[14]. This result differ from Acharya et al. (2010), where MES emerges to be informative with respect to the outcome of the stress test, and there are no differences in the results when switching from the generic stock index to the financial one. It has to be highlighted that the analysis presented in Acharya et al. (2010) refers to the US stress test of Spring 2009: the returns used for MES calculation cover roughly the previous year, which corresponds to the beginning of the crisis. In our analysis the period considered is less turbulent, and this could in principle explain the different results. However, as a robustness check, we calculate MES over the same period considered by Acharya et al (2010), and we do not find improvements in the informative contents of MES.

As a further robustness check, we also tried to calculate MES by using Eurostoxx50 as the reference index. In this case the results are slightly better: in the logit estimation the coefficient is 5% significant and the Mc-Fadden R^2 increases to about 12%but the improvement in terms of forecasting is negligible.

Table 3 The informative content of MES over Loss rate: OLS regression

Dependent variable: LOSS_RATE		
	(1)	(2)
Const	0.0359*** (0.0126)	0.0178** (0.0075)
MES	-0.0008 (0.0051)	
F_MES		0.0052 (0.00197)**
Leverage		
R-squared	0.0011	0.1273
Adj. R-squared	-0.0227	0.1066

Notes: 44 Observations; White standard errors; t-statistics in parenthesis;*,**,*** stand for 10%, 5%, 1% significance respectively

Table 4 The informative content of MES over Loss over capital: OLS regression

[13] Acharya and Steffen (2014a) compare SRISK estimates both to capital shortfall and total losses from EBA 2014. While there is no correlation with capital shortfall, there is a positive correlation with total losses suggesting that inconsistencies come from the capital ratio used. Our analysis differs in two ways: first we use a binary variable for undercapitalization instead of the absolute size of capital shortfall; second we compare MES and loss rates which are measures size- independent .

[14] This difference could derive from the design of the EBA stress tests, where feedback effects from the financial sector to the real economy are ignored, while they are captured in market data, as highlighted in Acharya and Steffen (2014).

Dependent variable: LOSS_CAP		
	(1)	(2)
Const	0.5696** (0.268)	0.2085 (0.1243)
MES	0.0529 (0.1135)	
F_MES		0.1576*** (0.0436)
Leverage		
R-squared	0.0077	0.208
Adj. R-squared	-0.0159	0.1891

Notes: 44 Observations; White standard errors; t-statistics in parenthesis; *,**,*** stand for 10%, 5%, 1% significance respectively

3.3 MES and F-MES vs ES

In order to understand the informative content of MES and F-MES with respect to the stress test results, we also tried the more traditional risk measure of expected shortfall (ES) as predictor. From results reported in Table 5, ES appears to work well in predicting the stress test results, being positively related to the three outcomes, always significant and highly so when it comes to the loss rate and the loss over capital.

Table 5 The informative content of Expected shortfall

	Dep. Var. DEF *Logit regression*		Dep. Var. LOSS_RATE *OLS regression*	Dep. Var. LOSS_CAP *OLS regression*
Const	-4.163878*** (-3.106573)	Const	0.021385*** (5.513056)	0.384244*** (4.938764)
ES	0.506989* (1.840442)	ES	0.002139*** (5.209915)	0.053188*** (4.903146)
Mc-Fadden R^2	0.283899	R^2	0.239294	0.263041
		Adj R^2	0.221182	0.245494

Notes: 44 Observations; z-statistics and t-statistics in parenthesis; *,**,*** stand for 10%, 5%, 1% significance respectively

Focusing on the prediction of capital shortfall (logit regression), in Figure 1 we show the estimated probability of capital shortfall versus the actual shortfall from stress tests. The capital shortfall is predicted by a high probability in the F-MES regression; the probability of capital shortfall is quite flat in the MES regression, which is clearly over-performed by the simple ES regression.

Figure 1 Probability of capital shortfall: a comparsion between ES and MES and F-MES

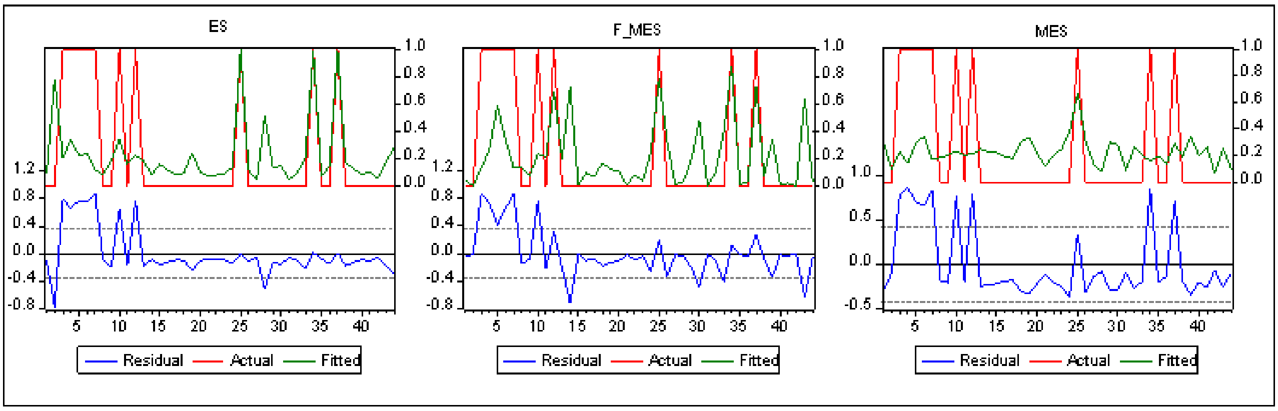

Table 6 presents the percentage of correct predictions with different cut-off value. The first and the second columns present the percentage of correct versus incorrect predictions over the cases of no shortfall and shortfall respectively; the last column presents the correct versus incorrect overall predictions. It emerges that, by fixing the cut-off at the standard 0.5 level, F_MES produces the highest percentage of correct overall predictions. Since MES delivers flat and low probability of capital shortfall, it correctly predicts all the positive no shortfall cases, but it performs very poorly in predicting the shortfall cases. We also fix the cut-off at 0.23 (about the actual percentage of shortfall in the sample): even if in this case ES produces the highest percentage of total correct prediction, F-

MES can capture 80% of the shortfall: if we are interested in a conservative output F-MES still performs better.

Table 6 Percentage of correct prediction from logit estimates for the three measure, by cut-off value

Cut-off 0.5	DEF=0	DEF=1	TOTAL
	MES as explanatory variable		
% Correct	100	10	79.55
% Incorrect	0	90	20.45
	F-MES as explanatory variable		
% Correct	94.12	50.00	84.09
% Incorrect	5.88	50.00	15.91
	ES as explanatory variable		
% Correct	94.12	30.00	79.55
% Incorrect	5.88	70.00	20.45
Cut-off 0.23	DEF=0	DEF=1	TOTAL
	MES as explanatory variable		
% Correct	61.76	50.00	59.09
% Incorrect	38.24	50.00	40.91
	F-MES as explanatory variable		
% Correct	79.41	80.00	79.55
% Incorrect	20.59	20.00	20.45
	ES as explanatory variable		
% Correct	88.24	60.00	81.82
% Incorrect	11.76	40.00	18.18

4. A comparison with the last 2016 EBA stress tests

To be completed.

5. Conclusions

Motivated by the strong connection between the actions undertaken by the regulators and the developments of the academic literature on systemic risk measures, in this paper we analysed the relationship between measures of systemic risk based on market data and the EBA stress test of the European banking system.

We focused on the measure known as MES, which was proposed by Acharya et al. (2010), and is defined as the average returns of a bank when the system (represented by a market index) exceeds VaR. The authors provide a theoretical background to justify the use of MES and present results on the goodness of this measure as predictor of the Supervisory Capital Assessment Program for the US banking system. In fact MES, capturing the fragility of a single bank in the presence of a crisis, lends itself to be confronted with regulatory stress test exercises. To the extent that regulatory stress test results can be predicted by relatively simple market-based measures, these measures can produce an important information for the market.

Our results for the 2014 EBA stress test of European banks are partially in contrast with the ones presented in Acharya et al. (2010). As for MES, we cannot find a significant relation between this risk measure and the outcomes of the EBA stress test. This conclusion is also in line with the critiques recently raised by Kupiec and Guntay (2015, p.27), who conclude that "MES measures may be incapable of reliably detecting a firm's systemic risk potential.". The lack of correlation between market based measure of systemic risk and stress test outcomes for European countries also emerges in Acharya et al (2014) and in Acharya and Steffen (2014), and the inconsistency seems to be related to the very same stress test design (Acharya et al. 2014). Specifically, Acharya and Steffen (2014) emphasize that the European Central Bank's calculation of shortfalls is based on capital ratio depending on risk-weights, which might not reflect the true risk of the banks' assets either in the internal or in the standard approach. In interpreting these results, it should also be underscored that some results for the US, which are supportive of MES as predictor, are estimated over a period of crisis, while for the European banking system the 2014 stress test refers to a less turbulent period.

We have also checked the robustness of our results with respect to another index as reference index (Eurostoxx50): although the relationship with MES becomes slightly significant, the improvement in terms of forecasting is negligible. This result is consistent with the fact that in European countries crises may stem from very different sources, and to accounted for this different indexes have to be used (as also stressed by Engle et al., 2015). However when we use a variation of MES that considers the financial sector as benchmark (F_MES), our results differ considerably. While in Acharya et al. (2010) both MES and F_MES have informative content in relation to the US stress tests, we find that only the latter measure is quite significantly related to the EBA 2014 stress test output. This difference in the information content between MES and F-MES hints to the idea that the adverse scenario depicted in the stress test pictures a crisis that is mainly a financial one. Finally, a comparison with a more traditional measure such as ES highlights that F-MES works overall better.

By moving to analyse the most recent 2016 EBA stress test, we find slightly different results. The differences are partly due to the very different sample of banks considered in the last exercise compared to the 2014 one.

Overall our results suggest that, when predicting stress test outcomes, the choice of the indexes to be used is very important in connection with the relevant scenarios. The disagreements in results obtained according to the use of different indexes may also reflect different aspects of systemic risk, which is difficult to define and even more to quantify in an univocal way. Concluding on the usefulness of this measures for regulators, we think that market based measures should be a complement rather than a substitute for regulatory stress tests.

References

Acharya, V., R. Engle, D. Pierret, 2014, "Testing macroprudential stress tests: The risk of regulatory risk weights", *Journal of Monetary Economics* 65, 36–53.

Acharya, V., R. Engle, M. Richardson, 2012, "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks", *American Economic Review Papers & Proceedings* 102:3, 59–64.

Acharya V., Pedersen L., Philippon T., Richardson M., 2010, "Measuring systemic risk", Technical Report, Department of Finance, Working Paper, NYU Stern School of Business

Acharya V., Steffen S., 2014 (a), "Making Sense of the Comprehensive Assessment", mimeo.

Acharya V., Steffen S., 2014 (b), "Benchmarking the European Central Bank's Asset Quality Review and Stress Test – A Tale of two Leverage Ratios", *Center for European Policy Studies*, Working Paper Series.

Adrian T., Brunnermeier M., K., 2011, "CoVaR", NBER Working Paper Series, N. 17454.

Altunbas Y., Manganelli S., Marques-Ibanez D., 2015, "Realized bank risk during the Great Recession", Board of Governors of the Federal Reserve System, International Finance Discussion Papers, n. 1140.

Banulescu G.-D., Dumitrescu E.-I., "Which are the SIFIs? A component expected shortfall approach to systemic risk", *Journal of Banking and Finance*, 50, 575-588.

BCBS, 2014, "The G-SIB assessment methodology. Score calculation" Bank of International Settlement.

Benoit S., Colliard J-E., Hurlin C., Perignon C., 2015, "Where the risks lie: a survey on systemic risk", HAL, halshs-01142014.

Bisias D., Flood M., Lo A. W., Valavanis S., 2012, "A survey of systemic risk analytics", Office of Financial Research, U.S. Department of the Treasury, Working Paper n.1, January 2012.

Black L., Correa R., Huang X., Zhou H., 2016, "The systemic risk of European banks during the financial and sovereign debt crises", *Journal of Banking and Finance*, 63, 107-125.

Bongini P., Nieri L., Pelagatti M., 2015, "The importance of being systemically important financial institutions", *Journal of Banking and Finance*, 50, 562-574.

Borio C., Drehman M., Tsatsaronis K., 2014, "Stress-testing macro stress testing: does it live up to expectations?", *Journal of Financial Stability*, 12, 3-15.

Borio C., Drehman M., 2009, "Towards an operational framework for financial stability: "fuzzy" measurement and its consequences", BIS Working Paper N. 284

Brownless C. T., Engle R., 2012, "Volatility, correlation and tails for systemic risk measurement", Working Paper, NYU Stern School of Business.

Daniellson J., James K. R., Valenzuela M., Zer I., 2015, "Can we prove a bank guilty of creating systemic risk? A minority report", SRC Discussion Paper N. 47.

De Bandt O., Heam J. C., Labonne C., Tavolaro S., 2013, "Measuring systemic risk in a post-crisis world", Debats Economique et Financiers N. 6, Banque de France.

Engle R., Jondeau E., Rockinger M., 2015, "Systemic risk in Europe", *Review of Finance*, 19 (1), 145-190.

Eijffinger S. C. W., 2009, "Defining and measuring systemic risk", European Parliament, IP/A/ECON/FWC/2009-040/C4

European Central Bank (ECB), 2009, "The concept of systemic risk", Financial Stability Review, 134-142.

Girardi G., Ergun T., 2013, "Systemic risk measurement: multivariate GARCH estimation of CoVaR", *Journal of Banking and Finance*, 37, 3169-3180.

Kupiec P., Guntay L., 2015, "Testing for systemic risk using stock returns", *AEI Economic Working Papers* 2015-02.

Lee J-H., Ryu J., Tsomocos D., 2013, "Measures of Systemic Risk and Financial Fragility in Korea", *Annals of Finance*, 9, 757-787.

Smaga P., 2014, "The concept of systemic risk", London School of Economics, SRC Special Paper Series N. 5.

Appendix A: List of banks tested by EBA and quoted

The table below summarizes the results of the EBA stress test (as from www.eba.europa.eu) on the banks in our sample. The Capital Shortfall is the difference between two components taken from the published EBA results: the required 5,5% capital required under the adverse scenario and the stressed capital. The variable is set to zero if this difference is negative. CETIER1 is the initial capital (Common Equity Tier 1 as from 31/12/2013) taken from the published EBA results. Total Loss is the sum of three components taken from the EBA published results: losses on the trading book and the banking book in the adverse scenario plus valuation losses due to sovereign shock. Quantities are expressed in Mln EUR.

Bank	Country	Capital Shortfall	CETIER1	Total Loss
Aareal Bank AG	Germany	0	2.187	398
Allied Irish Banks	Ireland	0	8.923	4.487
Banca Carige SpA	Italy	1.830	898	2.085
Monte dei Paschi di Siena SpA	Italy	4.250	5.687	10.327
Banca Popolare dell'Emilia Romagna	Italy	130	3.644	2.912
Banca Popolare di Milano	Italy	680	2.988	1.964
Banca Popolare di Sondrio	Italy	320	1.740	2.019
Banco Bilbao Vizcaya Argentaria SA	Spain	0	36.383	18.695
Banco BPI	Portugal	0	3.291	1.256
Banco Commercial Portugues	Portugal	1.140	4.667	3.426
Banco de Sabadell SA	Spain	0	8.217	4.629
Banco Popolare	Italy	690	4.234	5.972
Banco Popular Espanol SA	Spain	0	8.481	5.643
Banco Santander SA	Spain	0	56.086	40.843
Bank of Ireland	Ireland	0	6.549	4.327
Bankinter SA	Spain	0	2.781	1.642
Barclays Bank plc	UK	0	48.248	23.359
Bnp Paribas	France	0	65.508	32.692
Commerzbank AG	Germany	0	23.523	10.106
Credito Emiliano SpA	Italy	0	1.756	670
Danske Bank	Denmark	0	16.463	7.443
Deutsche Bank AG	Germany	0	47.312	15.199
DNB Bank Group ASA	Norway	0	13.683	3.664
Erste Group AG	Austria	0	10.173	8.572
Eurobank Ergasias	Greece	4.600	2.979	5.386
Group Credite Agricole	France	0	58.831	27.574

HSBB Holdings plc	UK	0	94.725	43.947
IKB Deutsche Industriebank AG	Germany	0	1.295	440
ING Bank NV	Netherlands	0	30.137	12.449
Intesa Sanpaolo SpA	Italy	0	33.333	23.045
Jyske Bank	Denmark	0	2.264	1.119
KBC Group NV	Belgium	0	11.777	6.119
Mediobanca	Italy	0	4.272	3.572
National Bank of Greece	Greece	3.430	4.262	7.857
Nordea Bank AB	Sweden	0	22.244	9.273
OTP Bank Ltd	Hungary	0	3.894	3.639
Piraeus Bank	Greece	660	5.959	4.422
Royal Bank of Scotland Group plc	UK	0	44.104	24.460
Societe Generale	France	0	366.333	19.261
Svenska HandelsbankenAB	Sweden	0	10.027	2.038
Swedbank AB	Sweden	0	8.890	2.106
SydbankAB	Denmark	0	1.307	639
Unicredit SpA	Italy	0	39.164	28.125
Unione di Banche Italiane	Italy	0	7.526	7.633

Source: www.eba.europa.eu

Appendix B: Definition of the variables used in the empirical analysis

Variable	Definition	Source original data
ES	Expected shortfall over the 5% percentile	Datastream (returns)
MES	Marginal expected shortfall calculated with respect to the MSCI Europe Index over the 5% percent	Datastream (returns)
F-MES	Marginal expected shortfall calculated with respect to the MSCI Europe Banks Index over the 5% percent	Datastream (returns)
LEVERAGE	Total Assets over Book Value of Equity	Datastream (returns)
DEF	Binary variable with value 1 when the capital under stress is below the required level	EBA
LOSS_RATE	Total loss under stress over total assets	EBA
LOSS_CAP	Total loss under stress over initial capital	EBA