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Systemic risk measures and macroprudential stress tests

An assessment over the 2014 EBA exercise

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Abstract

The European Banking Authority (EBA) stress tests, which aim to quantify banks' capital shortfall in a potential future crisis (adverse economic scenario), further stimulated an academic debate over systemic risk measures and their predictive/informative content. Focusing on marked based measures, Acharya et al. (2010) provides a theoretical background to justify the use of Marginal Expected Shortfall (MES) for predicting the stress test results, and verify it on the first stress test conducted after the 2007-2008 crises on the US banking system (SCAP, Supervisory Capital Assessment Program). 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 2014 European stress tests exercise conducted by EBA. Our results are strongly dependent on index used to capture the systemic distress event, whereby MES, based on a global market index, does not show association with EBA stress test, by contrast to F-MES, which is based on a financial market index, and has a significant information and predictive power. Our results may carry useful regulatory implication for the stress test exercises.

Keywords: systemic risk, stress test, macroprudential regulation

JEL: G01, G10, G28

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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 a unique definition of systemic risk, or a single risk measure. While different definitions can be found in the literature stressing different aspects[2], generally speaking systemic risk involves the whole financial system instead of the single institution and it spreads over the real economy. In line with this multiplicity of definitions, a wide range of measures have been developed for systemic risk.

Systemic risk by its nature involves both a cross-sectional and a time dimension[3], and available measures captures these two dimensions in different ways. Given the huge variety of measures, a classification of them is a difficult task. Recent surveys and classifications can be found in Bisias et al. (2012) and in De Bandt et al. (2013). Far from being exhaustive, we just sketch a rough picture of the most common measures. Firstly we can differentiate between measures based on the single bank, which mainly modify traditional risk measures to include contagion effects, and measures based on the system as a whole. As for the first group, measures 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 one hand measures of connectivity based on networks (graph theory) which focus on the cross-sectional dimension of risk only; on the other hand early warnings indicators which captures the time dimension.

The 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. Therefore, regulatory authorities have worked 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 risky 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.

[2] See e.g. Eijfinger (2009) and Borio and Drehman (2009) for a discussion and Smaga (2014) for a recent survey.

[3] These two dimensions have been discussed as for credit risk since the debate over procyclicality of Basel II developed: see e.g. Pederzoli and Torricelli (2005).

A literature on systemic risk measures and their connection with regulatory stress of the banking system has been developing in the latter few years. For example Acharya et al. (2012) proposed a capital shortfall estimation approach that can be used for the US stress tests required under the Dodd-Frank Act. Based on the 2011 U.S. and European stress tests, Acharya et al. (2014) compare capital shortfalls measured by the regulator to those of a methodology based on market data, and 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 .

Against this backdrop, in this paper we analyse the relation between systemic risk measures based on market data and stress test, and we propose and empirical assessment based on the October 2014 EBA stress test of the European banking system. In particular, 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 introduced by Adrian and Brunnermeier (2011) and Marginal Expected Shortfall (MES) proposed by Acharya et al. (2010). 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[4] of two generic institution and q the confidence level, $CoVaR_q^{j|i}$ is implicitly defined as

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

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

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:

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

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:

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

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 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 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[5]. 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.

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

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[6] 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:

- 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 do 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

[6] 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.

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 given DEF		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.[7] 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.

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

[7] For a robustness check we also performed a probit regression obtaining the same results.

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.[8] As for the Loss rate, the F-MES is again highly significant with the a positive sign as expected, while MES is not significant and even has the wrong sign.

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

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

[8] 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.

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, but only of 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. 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 explain the different results. As a robustness check we tried to calculate MES over the same period considered by Acharya et al (2010), but 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.

3.3 MES and F-MES vs ES

In order to understand the informative content of MES and F-MES, 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 overperformed by the simple ES regression.

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

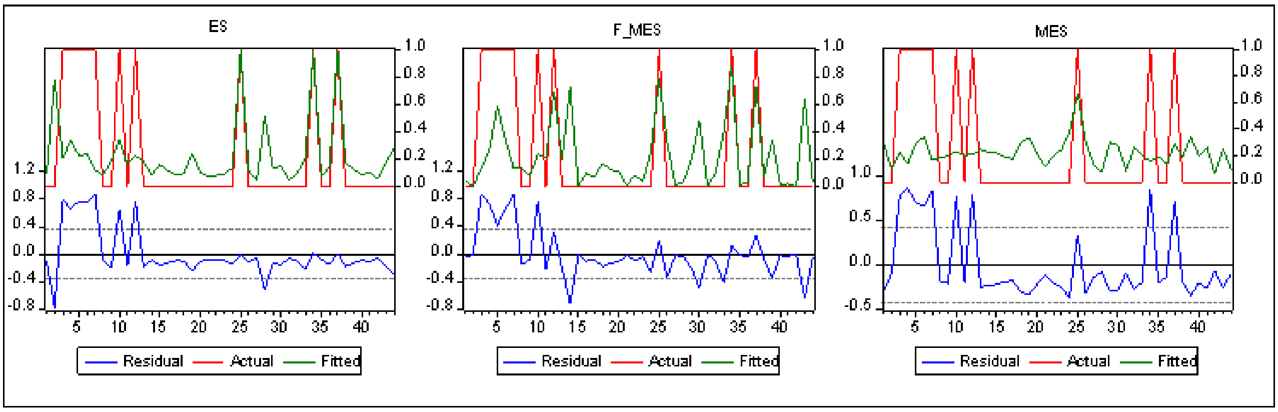

Table 6 presents the percentage of correct predictions with different cut-off value. The first and the second columns present the percentage of correct versus incorrect predictions over the cases of no shortfall and shortfall respectively; the last column presents the correct versus incorrect overall 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 Percent 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. Conclusions

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 published in October 2014. 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 a certain 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 on a crisis, lends itself to be confronted with regulatory stress test exercises.

Our results for the 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), who conclude that “MES measures may be incapable of reliably detecting a firm's systemic risk potential.". 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. 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 European stress tests, we find that only the latter measure is quite significantly related to the 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.

Before drawing conclusions, it should be stressed that results for the US supportive of MES are estimated over a period of crisis, while for the European banking system the latter stress test refers to a less turbulent period. Moreover, there is a more general point: the failure of market based measure may be related to the very same stress test design (Acharya et al. 2014). Specifically, Acharya and Steffen (2014) stress 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. Although further research is needed, these studies may carry useful regulatory implication for the stress test exercises.

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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	392	229
Barclays Bank plc	UK	0	2.781	1.642
Bnp Paribas	France	0	48.248	23.359
Commerzbank AG	Germany	0	65.508	32.692
Credito Emiliano SpA	Italy	0	23.523	10.106
Danske Bank	Denmark	0	1.756	670
Deutsche Bank AG	Germany	0	16.463	7.443
DNB Bank Group ASA	Norway	0	47.312	15.199
Erste Group AG	Austria	340	8.507	3.168
Eurobank Ergasias	Greece	0	13.683	3.664
Group Credite Agricole	France	0	10.173	8.572

HSBB Holdings plc	UK	4.600	2.979	5.386
IKB Deutsche Industriebank AG	Germany	0	58.831	27.574
ING Bank NV	Netherlands	280	237	540
Intesa Sanpaolo SpA	Italy	0	94.725	43.947
Jyske Bank	Denmark	0	1.295	440
KBC Group NV	Belgium	0	30.137	12.449
Mediobanca	Italy	0	33.333	23.045
National Bank of Greece	Greece	0	2.264	1.119
Nordea Bank AB	Sweden	0	11.777	6.119
OTP Bank Ltd	Hungary	0	33.659	27.188
Piraeus Bank	Greece	0	4.272	3.572
Royal Bank of Scotland Group plc	UK	3.430	4.262	7.857
Societe Generale	France	0	22.244	9.273
Svenska HandelsbankenAB	Sweden	30	435	261
Swedbank AB	Sweden	860	2.834	1.127
SydbankAB	Denmark	0	3.894	3.639
Unicredit SpA	Italy	850	2.155	1.303
Unione di Banche Italiane	Italy	660	5.959	4.422

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

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