Back-testing bank stress tests

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Abstract

We provide a first evaluation of the quality of banking stress tests that have become one of the main tool of banking regulation around the world. We propose a simple methodology to extract information from stress tests data. We estimate bank level exposures to macroeconomic risks, and we compare the prediction of our model to realized losses and to event-study market returns. We find that stress tests are informative. The model can predict realized losses of banks and market reactions to the release of macroeconomic news. We also find evidence that market participant learn from the stress tests.

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Stress tests have become a major tool of banking supervision in the United States and in Europe. Regulatory stress tests are used to set bank capital levels and validate dividend policies. The stress tests exercise mobilize large human and financial resources among regulators and among bankers. Regulators need to design the scenarios, run their own models, and monitor closely the answers provided by the banks. The banks, on the other hand, allocate considerable time and effort to estimating their stress test results.

Yet, despite the clear importance of stress tests, they have not been systematically analyzed. In fact, the data from the test are only used once, to give a pass/fail grade to the banks. The stress tests data are not back tested or used for other research. The issue of course is how to use the data, since the scenarios of the stress tests never actually happen. The central scenario should be close to the realized one on average but that is not very useful since we are precisely interested in deviations from this central scenario. The adverse scenarios, on the other hand, are much more interesting but they are, by definition (and thankfully) usually far from the realized one.

Our goal in this paper is to provide a first assessment of the quality of stress tests in Europe. We want to know whether stress tests results provide useful information on the resilience of banks to macroeconomic shocks, and whether market participants learn from these tests. To do so, we propose an approach in two steps. In a first step, we use the European stress test results to estimate bank loss rates sensitivity to macroeconomic shocks. Once we obtain these sensitivities, we compute loss rate predictions under actual macroeconomic events. These predicted loss rates can then be backtested against market and accounting data of banks.

Stress tests require banks to model loss rates on their credit exposures under a baseline scenario and under an adverse scenario. These scenarios cover all countries from the European Union. Banks report their projected losses for their main countries of exposure. We use the data from the exercise (i.e. the scenarios for macroeconomic factors – GDP growth, inflation, and unemployment rates – and loss rate projections reported by banks) to estimate bank sensitivity to macroeconomic shocks.

Our main results are as follows. First, we find that a simple model of bank loss rates exposure fits the stress results well. Second, we find that these estimated exposures predict relatively well

the realized losses of banks in subsequent years. Third, we estimate the market reaction of banks to macro announcement and we find that our estimated exposures help predict the cross sectional variation of bank stock returns after a macro announcement. We also find that these effects are stronger after the stress test is released, suggesting not only that stress tests contain information, but also that they contain new information, that was not fully known by market participants before the tests.

Overview of the EBA 2014 stress tests In 2014, the European Banking Authority (EBA) conducted Euro-wide stress tests on 123 banks covering approximately 80% of total banking assets in the EU [EBA, 2014].[1] The EU-wide stress test was coordinated by the EBA across the EU and is carried out in cooperation with the European Systemic Risk Board (ESRB), the European Commission, the European Central Bank (ECB), and the relevant national regulators. The various tasks involved in the stress tests were split as follows. The ECB was responsible for the overall quality assurance and for the asset quality review that provides the starting point of the stress test. The ESRB and the European Commission provided the underlying macroeconomic scenarios. The EBA developed the common methodology and ensured the disclosure of the results. The ECB and the national authorities could decide follow up actions.

The starting point of the stress test is the balance sheet of banks at end of december 2013. Two macroeconomic scenarios are constructed for the 2014-2016 horizon: a baseline scenario, and an adverse scenario. Macroeconomic and financial variables (GDP growth, HICP inflation, unemployment, interest rates, stock prices, house price and funding) are projected in the adverse scenario in terms of deviations from the baseline scenario. Each bank must then apply the shocks of the scenario to its portfolio and to generate credit, market and funding losses.

Under the adverse scenario the average CET1 ratio decreases by 3 percentage points. The CET1 capital decreases by 182 billion whereas loan losses represent 362 billion. 25 institutions failed to the Comprehensive Assessment (Asset Quality Review and Stress Test). The corresponding capital shortfall amounted to 25.2 billion.

[1]The total assets of banks participating to the exercise represent almost 22 trillion (approximatively 82% of the banking system covered).

Literature Review There is a growing theoretical literature on assets quality reviews and stress tests. Several recent papers study specifically the trade-offs involved in revealing information about banks. Goldstein and Sapra [2014] review the literature on the disclosure of stress tests results. Goldstein and Leitner [2013] focus on the Hirshleifer [1971] effect: revealing too much information destroys risk-sharing opportunities between risk neutral investors and (effectively) risk averse bankers. These risk-sharing arrangements also play an important role in Allen and Gale [2000]. Shapiro and Skeie [Forthcoming] study the reputation concerns of a regulator when there is a trade-off between moral hazard and runs. Other papers, such as Bouvard et al. [2015] and Parlatore [2013], study disclosure in models of bank runs using the global game approach of Carlsson and van Damme [1993] and Morris and Shin [2000]. Faria-e Castro et al. [2014] study a model of optimal disclosure where the government trades off Lemon market costs with bank run costs.

There is much less work on the empirical side. In particular, no paper has attempted to evaluate the quality of stress tests. Glasserman and Tangirala (2015) evaluate one aspect of the relevance of scenario choices in U.S. stress tests. They show that the results of U.S. stress tests are somewhat predictable, in the sense that the ranking across banks of projected stress losses in 2013 and 2014 are correlated. Similarly, the rankings across scenarios in a given year. They argue that this suggests that regulators should experiment with more diverse scenarios, so that it is not always the same banks that project the higher losses. But these results refer only to reported results and they do not speak to the quality of the results themselves.

1 Model

1.1 Estimating loss rates sensitivity to macroeconomic shocks

We are interested in estimating the sensitivity of bank losses to macroeconomic shocks. Stress tests require banks to model loss rates on their credit exposures under a baseline scenario and under an adverse scenario. We use the data from the stress tests to estimate bank sensitivity to

macroeconomic shocks. These scenarios cover all countries from the European Union.[2] Banks reported their projected losses for their main countries of exposure.

The first point to understand is that what we call a "scenario" is in fact a set of scenarios because each country in the EU is subject to different macro-economic scenarios. The units of observation in our model is therefore:

- name of the bank $i \in [1:123]$
- scenario $s \in \{\text{baseline, adverse}\}$ and projection year $t = \{2014, 2015, 2016\}$
- country of operation $i \in [1:21]$
- portfolio $p \in \{\text{retail, corporate, ..}\}$

We can define a scenario as follows

Definition 1. A **scenario** s is a sequence of vectors $y^s_{j,t}$, representing the macroeconomic factors in country j at time t.

In our application, we will use the following macro-variables

$$y^s_{j,t} = \begin{pmatrix} g^s_{j,t} \\ \pi^s_{j,t} \\ u^s_{j,t} \end{pmatrix}$$

where g is the growth rate of GDP, π is inflation, and u is the unemployment rate, in country j at time t under scenario s. The vast majority of banks included in the stress test exercise have branches or subsidiaries in several countries. They report loss rates on various portfolios and countries.

Definition 2. The **results** of the stress tests is a set of loss rates $l^{s,p}_{i,j,t}$ representing the losses for portfolio p of bank i in country j at time t under scenario s.

Finally, a model is a mapping from scenarios to loss rates

[2]These scenarios also cover a large list of countries outside the EU but only for two macroeconomic factors: GDP growth and inflation. We do not include countries outside the EU in our analysis.

Definition 3. A **model** of portfolio losses is a mapping from $y^s_{j,t}$ to $l^{s,p}_{i,j,t}$

$$l^{s,p}_{i,j,t} = F_{p,i,j}\left(y^s_{j,t}\right)$$

It is clear that different portfolios (retail, corporate) are sensitive to different macroeconomic shocks, so the mapping should obviously depend on p. In theory, we could imagine that the credit loss rate sensitivity to macroeconomic shocks could also depend on the specific {bank, country} pair. For instance, it is conceivable that the retail portfolio of BNP in France has a different sensitivity to French GDP than the retail portfolio of BNP in Italy to the Italian GDP. Unfortunately, if we do not restrict the model, we would potentially end up with $3 \times 21 \times 123 = 7749$ degrees of freedom. We therefore estimate the following restricted specification for losses on portfolio p:

$$\log \frac{l^{s,p}_{i,j,t}}{1 - l^{s,p}_{i,j,t}} = \alpha^p_{i,j} + \beta^p_i \times \left(\theta^p_j \cdot y^s_{j,t}\right) + \epsilon^{s,p}_{i,j,t} \tag{1}$$

We allow for a {bank, country} average quality $\alpha_{i,j}$. If all banks were active in all countries, this would be $28 \times 123 = 3567$ coefficients. The next term is the macro-sensitivity. It has two components. First, $\theta^p_j \cdot y^s_{j,t}$ creates a macro factor for country j (i.e., θ^p_j and $y^s_{j,t}$ are both vectors of size 3, and their product is a scalar). This corresponds to $3 \times 28 = 84$ coefficients. The macro factor summarizes the macro scenario for country j. Then we allow for a bank specific exposure β^p_i, which can capture differences in risk management across banks. This corresponds to 123 coefficients.

1.2 Using the model to predit actual outcomes

The second step of our analysis is to use the estimated model to predict actual outcomes. We consider two kinds of outcomes: realized losses and news shocks.

1.2.1 Realized losses

Let $Y_t \equiv \{y_{j,t}\}_{j=1..28}$ be the actual realization of the macro variables. One issue is that the disclosure of realized losses is not as granular as the disclosure of stress tests projections. In particular, banks report *consolidated* losses, across their various subsidiaries in different regions. With the model

estimated in equation (1), we can predict loss rates on portfolio p

$$\mathbb{E}\left[L^p_{i,t} \mid Y_t\right] = \sum_{j=1}^{21} \frac{\exp\left(\hat{\alpha}^p_{i,j} + \hat{\beta}^p_i \hat{\theta}^p_j \cdot y_{j,t}\right)}{1 + \exp\left(\hat{\alpha}^p_{i,j} + \hat{\beta}^p_i \hat{\theta}^p_j \cdot y_{j,t}\right)} \times EXP^p_{i,j} \tag{2}$$

where $EXP_{i,j}$ is the exposure of bank i to country j.

These predictions can then be backtested against realized losses by running the following regression

$$\frac{L^p_{i,t}}{Loans_{i,p,t}} = \alpha_0 + \delta \frac{\mathbb{E}\left[L^p_{i,t} \mid Y_t\right]}{Loans_{i,p,t}} + \varepsilon_{i,t} \tag{3}$$

1.2.2 News shocks

There are two limitations with using realized losses. One is statistical power: we have to wait for the macro scenario to materialize and then we only get one observation per bank. The other limitation is that we do not know if market participants actually learn from the stress tests.

To overcome these limitations, we also compare market reactions to macroeconomic releases as a function of our estimated exposure. The change in loss expectation is computed as the difference between loss expectation with the macroeconomic news and the loss expectation with the economists' consensus provided by Bloomberg. Consider the release of a macro series at time τ. Let y_{j,τ^-} be the consensus just before the release, and let y_{j,τ^+} be the consensus just after the release. According to our model, the change in the expected losses for bank i is given by

$$\Delta_\tau \mathbb{E}\left[L_{i,\tau}\right] = \sum_{j=1}^{21} \left(\frac{\exp\left(\hat{\alpha}^p_{i,j} + \hat{\beta}^p_i \hat{\theta}^p_j \cdot y_{j,\tau^+}\right)}{1 + \exp\left(\hat{\alpha}^p_{i,j} + \hat{\beta}^p_i \hat{\theta}^p_j \cdot y_{j,\tau^+}\right)} - \frac{\exp\left(\hat{\alpha}^p_{i,j} + \hat{\beta}^p_i \hat{\theta}^p_j \cdot y_{j,\tau^-}\right)}{1 + \exp\left(\hat{\alpha}^p_{i,j} + \hat{\beta}^p_i \hat{\theta}^p_j \cdot y_{j,\tau^-}\right)} \right) \times EXP_j \tag{4}$$

These predictions can then be backtested against market reactions by comparing the excess return of bank i at time τ to the predicted losses

$$r_{i,\tau} = \alpha_0 + \gamma \frac{\Delta_\tau \mathbb{E}\left[L_{i,\tau}\right]}{CET1_i} + \vartheta_\tau + \varepsilon_{i,\tau} \tag{5}$$

where $CET1_i$ is the core equity tier 1 of bank i.

2 Data

We gather four types of data: the EU 2014 stress test results, macroeconomic publications, bank market and accounting data.

2.1 Stress Test Data

We focus our analysis on corporate and retail portfolios which represent by far the largest share of bank credit activities. In addition, the credit block displays balance sheet by main countries of exposure. Each bank breaks down its credit exposures up to the 10 largest countries of exposure of its banking book. For each country of exposure, the data provides information on bank loss rate in each year over the horizon 2014-2016. The exercise is conducted under two scenarios defined by the EBA: a baseline scenario – which reflects the expected macroeconomic conditions to be realised in the country of exposure in the next 3 years – and an adverse scenario – which reflects an extreme but plausible deterioration in macroeconomic conditions over the same period. Thus for a bank, in a given country of exposure, we have 6 observed loss rates and macroeconomic shocks for the corporate and retail portfolios.

We first build an econometric model of the banks' projected losses on the loan portfolio using the main macroeconomic variable. We then assess the predictive power this model as explained earlier. The credit block of the exercise discloses balance sheet exposures of banks to different asset classes in the banking book: central banks and central governments, institutions, corporates and retail.

Our main input is the publicly disclosed European stress test results.[3] This publication gives access to information on 123 European banks. The stress test is divided in different blocks reflecting the main risks in banks' balance sheets. We focus on the credit risk block as it discloses a very rich set of data to estimate bank sensitivity to macroeconomic shocks: credit exposures by asset classes and country as well as associated loss rates in each scenario/year.

[3]See www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2014/results

2.2 Macroeconomic publications

Our aim is to test whether stress test results contain useful information on bank sensitivity to macroeconomic shocks. For this purpose, we calibrate a model of loss from the stress test data and input real macroeconomic events. We collect information on macroeconomic publications to predict loss rates under these actual figures. We consider two types of publications: macroeconomic announcements above or below consensus to model unexpected losses and harmonised macreconomic series from the European statitstical institute (Eurostat) to predict expected losses.

Data on macroeconomic announcements above or below consensus – which we define as unexpected macroeconomic shocks – are collected from Bloomberg. Unexepected macroeconomic shocks are the relevant inputs when we compare the model prediction with market prices. Indeed, an expected event should not trigger price variation at the moment of publication. Only unexpected announcements should affect banks' stock price. We start by collecting all announcements for each EU country over 2013-2014. Bloomberg references 15,470 economic announcements for all European Union countries. We are interested in the date, country, nature of the macroeconomic announcement and the economist forecast as published by Bloomberg (which is the median of a panel of economists' forecast). The model we calibrate from stress test data only relies on three macroeconomic factors: GDP growth, inflation and unemployment rates. Thus, we only retain year-on-year real GDP growth, unemployment rate and year-on-year inflation rate publications. The number of publications drops to 2,148. We then eliminate all publications where the consensus equals the actual figure as they should not represent an element of surprise for the market. We also drop publications where no consensus was published because we cannot quantify the surprise of the publication for the market. Finally, we compute the unexpected macroeconomic shock as the difference between the actual published figure and the forecast. Our final set of announcements contains 949 publications of unexpected macroeconomic shocks.

To compare model predictions with accounting credit losses, we need the full value of the macroeconomic indicators and not only their elements of surprise. We then also collect Eurostat harmonised macroeconomic series for EU countries from 2013 to June 2015. These series are used to compare the model predictions with accounting credit losses. As before, we only retain

publications of real gdp growth, inflation and unemployment rates.

2.3 Bank market and accounting data

Our sample comprises 58 listed banks. Bank equity price are collected on Bloomberg. We then compute the daily return for all listed banks of our sample. For accounting data, we rely on two different sources: bankscope and the EBA 2015 transparency exercise. The EBA 2015 transparency exercise reports financial accounts of a sample of EU banks close to the sample of banks included in the 2014 stress test exercise.[4] For each data source, we collect the loan loss provisions to be compared with the model predictions. We collect total loans in Bankscope to normalize losses between banks. The EBA transparency exercise displays credit risk exposures. We use annual accounts in bankscope for 2013 and 2014, meanwhile the transparency exercise reports financial results of banks for end of 2014 and June 2015. Apart from the difference in publication date of financial accounts, Bankscope and the EBA transparency exercise differ in the perimeter of consolidation of banks. Bankscope report banks' account for their full perimeter of activity. This can notably include insurance activities that represent, for certain bank holding companies in Europe, a non trivial share of their total assets. The EBA transparency exercise reports financial accounts on the same perimeter as for the stress test, i.e. it focuses exclusively on banking activities. The EBA data covers the same exposure types as the stress test exercise, i.e. all assets and off-balance sheet commitments which are treated under credit risk in the prudential regulation. Bankscope and the EBA transparency exercise cover, respectively, 116 and 103 banks from the stress test exercise.

[4]For more details on the transparency exercise, see `https://www.eba.europa.eu/risk-analysis-and-data/eu-wide-transparency-exercise/2015/results` www.eba.europa.eu/risk-analysis-and-data/eu-wide-transparency-exercise/2015/results

3 Results

3.1 Bank loss rate sensitivity

We start by estimating the bank loss rates sensitivity to the macroeconomic scenarios. Relying on the stress test results, we need to estimate the paramaters $\alpha_{i,j}^p$, β_i^p and θ_j^p in equation (1) in order to map macroeconomic shocks into bank losses. We estimate the parameters separately for the corporate and retail portfolios. For the corporate portfolio, we have 3,148 loss rates observations, each corresponding to a certain stress test scenario in a certain country of exposure. Correspondingly, we have 2,760 observations for the retail portfolio. Given that we would like to obtain 123 β_i^p $\times$ 28 $\theta_j^p\times$ 3 macroeconomic factors (GDP growth, inflation and unemployement rates), estimating the model in one step is not feasible. Consequently, we adopt a strategy in two steps where we start by fixing β_i^p equal to 1. We then estimate the model in equation (1) to obtain estimates for θ_j^p. For the corporate portfolio, the model thus estimates 531 $\alpha_{i,j}^p$ parameters plus 84 θ_j^p parameters. In the same vein, the model estimates another set of 464 $\alpha_{i,j}^p$ and of 84 θ_j^p parameters for the retail portfolio. For each portfolio, we then compute the macro factor as the product of the estimated $\hat{\theta}_j^p$ with the macroeconomic scenario $y_{j,t}^s$. In a second step, we can now estimate - for each portfolio again - the set of $\alpha_{i,j}^p$ and β_i^p parameters. That is we estimate 531 $\alpha_{i,j}^p$ plus 123 β_i^p parameters for the corporate portfolio. Similarly, we estimate 464 $\alpha_{i,j}^p$ plus 123 β_i^p parameters for the retail portfolio.

Table 1 presents synthetic information on the estimation of bank loss rate sensitivity to macroeconomic shocks. Given the important number of parameters estimated, we do not report the coefficients of the regressions. We can see from the table that our restricted model is able to capture virtually all the information contained in the stress test results. For GDP growth, the coefficients are significantly negative for, respectively, 26 countries and 21 countries in the corporate and retail portfolios. The negative sign indicates that an increase in GDP growth is related to lower losses for banks. The coefficients for inflation rate are only significant in 13 countries for the corporate portfolio and 15 countries for the retail portfolio. The sign of the coefficients varies between countries. Among other reasons, this reflects the fact that in some European countries, banks mostly

set credit conditions in fixed interest rates, whereas in other countries banks massively rely on floating rates when they grant credit. It is thus not surprising to observe different coefficient signs and level of statistical significance between countries. For the unemployment rate, coefficients are only significant in 13 countries for the corporate portfolio and 12 for the retail portfolio. Almost all significant coefficients are of positive sign indicating that an increase in unemployment is related to an increase in loss rates. We interpret the relative lack of significance on the unemployment rate coefficients as a consequence of the high (negative) correlation between GDP growth and unemployment rates. Because both of these indicators reflect the underlying strength of the economy, they contain a large share of similar information.

The β_i capture the sensitivity of banks to a global macroeconomic shock. For each bank, we thus obtain a different sensitivy to a global shock on GDP growth, inflation and unemployment rates. Table 2 shows the weighted average loss rate sensitivity by banks' country of origin. Note that there are only 23 countries of origin in the stress test exercise (i.e. only foreign subsidiaries of large banking groups operate in some countries of exposure). The β_i are obtained from the estimations in step 2 (see table 1) after normalizing the $\hat{\theta}_j^p$ by the coefficient obtained for GDP growth in France. Bank sensitivities to macroeconomic shocks differ significantly depending on banks' country of origin. For a given quality of the portfolio of a bank in a country of exposure (captured in our model by the $\alpha_{i,j}^p$ parameters), a higher β_i in absolute terms indicate a greater sensitivity to the global macroeconomic factor.

The model estimated in this first part allows us to map loss rates to macroeconomic shocks. With the estimated parameters, we can now backtest the stress test model with banks' realized losses and news shocks. To do so, we compute the expected losses under the actual realization of the macro variables for different available years. We also compute the change in expected loss after macroeconomic news are released to market reactions.

3.2 Sample descriptive statistics

We present statistics on collected balance sheet and market data on our sample of banks, as well as the model predictions under the macroeconomic realizations and market news. The dataset is

split in two group of banks: those applying the static balance sheet assumption in the stress test and those relying on a dynamic balance sheet assumption.

3.2.1 Static balance sheet vs. dynamic balance sheet

The European stress test was carried out under a general assumption of static balance sheets. This assumption implies that no asset growth is possible over the 3 years horizon of the test. Maturing assets during the exercise are assumed to be replaced with similar exposures in terms of type, credit quality and maturity at the start of the exercise. Finally, no replacement or write-down of defaulted assets is allowed in the exercise.

However, some banks carrying the exercise in 2014 were subject to a restructuring plan approved by the European commission before December 2013 – the starting date of the stress test. These restructuring plans concern 32 banks in the stress test exercise which received state support (e.g. government recapitalization) in the aftermath of the 2008 financial crisis. These banks were authorized to apply a dynamic balance sheet assumption on the troubled assets they were supposed to cut-off under the restructuring plans. Given the nature of banks under this assumption and the fact that they could diminish their exposure on troubled assets in the exercise, we consider them separately from the other group of banks in our backtesting framework.

3.2.2 Realized losses and macroeconomic news statistics

Table 3 presents sample descriptive statistics. We start by comparing descriptive statistics for realized losses and model expected losses in the static balance sheet group of banks. Bankscope data covers the end of year 2013 and 2014. Meanwhile the EBA transparency exercise covers December 2014 and June 2015. Interestingly, we see that descriptive statistics between realized losses and the model predictions appear to be in line. With bankscope, the median expected losses are equal, meanwhile they are very close with the EBA transparency data. The mean and maximum losses are also in a comparable range (for the mean, they exactly match with EBA realized losses data). Finally, standard deviation also appear comparable. If we turn to banks with the dynamic balance sheet assumption, conclusions are very much alike.

Concerning the market news, the range of the model predictions and equity return cannot be directly compared. We observe that on average over the period the equity return is close to 0 but slightly negative for static balance sheet banks at -0.01%. The average change in loss expectation is positive. For dynamic balance sheet banks, the average equity return is interestingly positive at 0.21% over the period and the change in loss expectation is slightly lower albeit comparable to the one of banks with static balance sheet in the stress test.

3.3 Realized losses

3.3.1 Stress test model predictions compared to Bankscope data

We start our backtesting of stress test models by comparing loss predictions with realized losses. We use Eurostat harmonised macroeconomic indicators to predict accounting losses on a yearly basis with our model in equation (2). We compare the predictions with loan loss provisions reported by banks in their profit and loss account. Both losses predictions and accounting loan loss provisions are normalised by bank loan portfolios at the end of the corresponding year. Table 4 reports the regressions of loan loss provisions over model predictions.

Column (1) and (2) include the whole sample of banks using the static balance sheet assumption in 2013 and 2014. We start in column (1) with a pooled OLS model and include a year dummy in column (2) to control for the average losses in the two periods. The OLS model shows that predicted losses are highly and positively correlated with loan loss provisions. This test on accounting data is a first proof that the stress test model contain relevant information on bank resilience to macroeconomic shocks. On average, an increase of 1 p.p in model losses is related to an increase of 1/3 p.p realized losses. Thus, stress test models tend to over-estimate the effect of macroeconomic shocks on banks' losses. This result is not necessarily surprising given that parameters are estimated under extreme scenarios. Thus they reflect bank sensitivity to extreme shocks, much larger than the actual macroeconomic inputs we use in 2013 and 2014.

Next, we analyze how the model is able to predict realized losses in the cross-section. Columns (3) and (4) present results of the model respectively for 2013 and 2014. The coefficient of interest remains at the same magnitude, about one-third. However, the standard-error is much larger in

2013, making the estimate non-different from zero. In contrast, the model predictions remain significantly positive in 2014.

Finally, column (6) tests the same model on the subsample of banks applying the dynamic balance sheet assumption. Given the small size of the sample, we only report the pooled regression (results remain statistically significant when we split the sample by year). We observe that these banks' predictions are also highly correlated with their realized losses. Interestingly, we do not find that stress test models over-estimate these banks' losses. The coefficient is not statistically different from 1 in column (5).

3.3.2 Stress test model predictions compared to EBA 2015 transparency data

In 2015, the EBA publicly released a transparency exercise for a panel of banks close to the one of the stress test exercise.[5] This exercise includes the publication of bank accounting data for two periods: December 2014 and June 2015. The data released correspond to banks (usually) confidential reporting to their supervisor. The perimeter of activity under which bank losses are reported in this EBA exercise is the same as in the stress test: it is limited to banking and exclude other financial activities such as insurance which might impact losses reported in Bankscope. The perimeter is also perfectly in line in terms of exposure type as in the stress test. That is, exposures correspond to credit risk exposure, a concept larger than the loan portfolio as it includes off-balance sheet commitments and some debt securities. We collect loan loss provisions reported by banks and compute the predicted losses for the corresponding sample. We use Eurostat yearly macroeconomic indicators for December 2014 and compute year-on-year GDP growth, inflation rate from quarterly figures for June 2015. We also use the unemployment rate figure in June 2015. The results are reported in table 5.

Columns (1) to (2) reports the estimates of the model for banks with static balance sheet with both period pooled together. Column (2) include a year dummy to control for a potential time effect on the results. As with Bankscope data, we again find strong evidence that the stress test model predictions are in line with realized losses. The expected losses are significantly and positively related to actual loan losses. Interestingly, the coefficient is now much higher with

[5]For more details, see www.eba.europa.eu/risk-analysis-and-data/eu-wide-transparency-exercise/2015/results

the EBA data. This is presumably due to the perfect alignement between the stress test model perimeter in terms of exposures and the EBA transparency data. Column (3) reports the results for December 2014. This time, the coefficient is not statistically different from 1 (and strongly different from 0). In column (4), the realized losses are regressed for the subsample of observations in June 2015. We obtain a positive and significant coefficient which is not statistically different from 0.5. Given that over half a year, one can assume that a bank losses approximately half of a year losses, this result is consistent. When we rely on EBA loss data, we thus do not find anymore that stress test models are over-estimating losses for "normal" shocks.

Column(5) presents again results for the subsample of banks with the dynamic balance sheet assumption. We again find a positive associatio between model loss prediction and the realized losses of this subgroup of banks.

Overal our results show that stress test results provide a useful information on banks' ability to withstand shocks. They are based however on a relatively small sample of observations. They also do not provide any information on what the market learns from stress test exercises. To overcome this limitation, we propose in the next section to compare market reactions to the change in expected losses at macroeconomic releases.

3.4 Stress test model predictions and news shocks

Here, the backtesting exercise compares the predicted unexpected losses obtained from equation (4) with bank equity daily return. Table 6 reports regressions of bank equity daily return on the predictions based on model obtained from stress test data. The change in expected losses is obtained by comparing the deviation between the expected losses after the macroeconomic release to the expected loss under the economists' consensus provided by Bloomberg. Compared to our previous sample, we can only include 43 listed banks in the static balance sheet assumption sample and 15 banks in the dynamic balance sheet assumption sample.

The first 6 columns of the table deal with banks using the static balance sheet assumption during the stress test. The last column reports results for banks using the dynamic balance sheet assumption. In the different estimations, we add various fixed effects to account for potential

heterogeneity potentially biasing the results. We start in column (1) with a simple OLS model without any fixed effects. We observe that unexpected losses predicted from the model are indeed negatively correlated with banks' equity return. The coefficient is strongly significant at the 1% level. To take into account common shocks between banks at the announcement dates, column (2) includes date fixed effects. The OLS regression in column (1) could indeed only capture the fact that banks have on average negative returns when there are bad news. When we include date fixed effects, the coefficient of interest remains significantly negative. This result indicates that, given a common shock to banks, the model estimated from the stress test results is able to differentiate the degree of intensity of the shock between banks. Said differently, the estimated parameters allow us to classify on average banks' loss rates after a macroeconomic shock. We continue to remove heterogeneity in the estimation by including country of origin fixed effects in column (3). The main coefficient remains significant with the expected negative sign. When we control for country heterogeneity, we are still able to distinguish banks' sensitivity to a macroeconomic shock. Finally, column (4) goes one step further by including bank fixed effects. We still find that bank heterogeneity does not bias the results. The coefficient remains unchanged from the first three columns.

In columns (5) and (6), we split the sample by year. Column (5) reports the results for announcements in 2013 meanwhile column (6) do so for 2014. We find that our results are driven by 2014. The coefficient is non-different from 0 in 2013 and significantly negative in 2014. That year the estimated coefficient doubles compared to the full sample regressions. Given that the stress test exercise was carried out in mid-2014, this result might indicate that market are learning new informations on banks' strength from the stress test.

Finally, in column (5) we conduct the same analysis on the sample of banks using a dynamic balance sheet hypothesis in the stress test exercise. Here, we do not find that the predicted losses are correlated with equity return. Results are unchanged when we split the sample between 2013 and 2014. We thus do not find evidence that the model predictions are able to match market data after unexpected macroeconomic shocks. Thus, all in all we find mixed evidence for banks with dynamic balance sheet assumption. One has however to keep in mind that the group of banks was

larger and more heterogeneous in the previous section comparing model predictions to realized losses. The listed banks among banks with dynamic balance sheet assumptions[6] are larger banks with past problems well known from the market. It is thus possible that the stress test reveals less information on these banks given their high level of scrutiny by the market.

4 Robustness

Our backtesting relies on some important assumptions. To build confidence in our results, we plan to conduct several robustness checks.

- Enlarge the selected macroeconomic indicators by including PMI announcements.
- Conduct a placebo test with market data
- Consider bank CDS return as an alternative indicator to backtest model predictions.
- Control for leverage effects in the market return regressions.

5 Conclusion

Regulatory stress tests conducted extensively on banks in the Eurozone involve detailed investigation of bank solvency and resilience under different marcoeconomic conditions inclduing, but not limited to, severe adverse scenarios. However, there is very limited back-testing of such data. We provide the first assessment of of the quality of stress tests in Europe. We want to know whether stress tests results provide useful information on the resilience of banks to macroeconomic shocks, and whether market participants learn from these tests.

Our main results are as follows. First, we find that a simple model of bank loss rates exposure fits the stress results well. Second, we find that these estimated exposures predict relatively well the realized losses of banks in subsequent years. Third, we estimate the market reaction of banks to macro announcement and we find that our estimated exposures help predict the cross sectional

[6]These are RBS, Lloyds, AIB, Bank of Ireland, Alpha Bank, National Bank of Greece, Eurobank Ergasias, Piraeus Bank, BCP Portugal, Caixa Bank, Banco de Sabadell, Commerzbank, Dexia, MPS, Bank of Cyprus

variation of bank stock returns after a macro announcement. We also find that these effects are stronger after the stress test is released, suggesting not only that stress tests contain information, but also that they contain new information, that was not fully known by market participants before the tests.

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Table 1 Estimation of bank loss rate sensitivity to macroeconomic shocks

We estimate the model presented in equation (1) in two steps. First, we set $\beta_i = 1$ in order to estimate the θ_j^p parameters. In a second step, we use $\hat{\theta}_j^p \cdot y_{t,j}^s$ to estimate the β_i parameters of the model. The table shows which parameters are included in each step and the respective adjusted R^2 of the model.

	$\log \frac{loss\ rate}{1-loss\ rate}$			
	First step: Setting $\beta_i = 1$		Second step: Using $\hat{\theta}_j^p \cdot y_{t,j}^s$ from step 1	
	Corporate portfolio	Retail portfolio	Corporate portfolio	Retail portfolio
	(1)	(2)	(3)	(4)
α parameters	Y	Y	Y	Y
# of parameters	531	464	531	464
θ paramaters	Y	Y	N	N
# of parameters	84	84		
β parameters	N	N	Y	Y
# of parameters			123	123
Adjusted R^2 (%)	99.7	99.6	99.8	99.7
Observations	3,148	2,760	3,148	2,760

Table 2 β_i by banks' country of origin

Weighted average of β_i by total assets in 2014. The β_i are obtained in step 2 of the regression of equation (1) after normalizing the $\hat{\theta}_j^p$ by the coefficient for GDP growth in France.

	Weighted average of β_i	
Country of origin	Corp. portfolio	Retail portfolio
All countries	-20.95	-15.55
AT	-15.94	-13.19
BE	-15.84	-10.82
CY	-16.38	-14.85
DE	-18.15	-11.48
DK	-17.65	-19.50
ES	-15.62	-16.27
FI	-30.09	-24.85
FR	-19.04	-19.40
GR	-18.54	-16.41
HU	-21.37	-18.78
IE	-27.84	-13.20
IT	-17.14	-17.07
LU	-24.21	-19.45
LV	-16.26	-14.68
MT	-21.88	-16.23
NL	-17.48	-17.51
NO	-36.58	-18.77
PL	-20.23	-18.59
PT	-17.38	-21.53
SE	-19.40	-13.29
SI	-15.21	-16.03
UK	-30.99	-13.17

Table 3 Descriptive statistics

Static (Dynamic) Balance Sheet columns refer to banks relying on the static (dynamic) balance sheet assumption in the stress test exercise. *Loan provisions / Total loans (Bankscope)* is the ratio of loan loss provisions over total loans from Bankscope in december 2013 and 2014. *Loan provisions / Credit exposures (EBA Transparency 15)* is the ratio of loan loss provisions over total credit risk exposures from the EBA 2015 transparency exercise.*Exp. losses* is the model prediction of loan losses with Eurostat macroeconomic figures for GDP growth, inflation and unemployment rates. $\triangle$*Exp. losses / CET1* is the difference between the model loss prediction after a macroeconomic release and the model loss prediction with the economists' consensus from Bloomberg over common equity tier1 of the bank.

	Static Balance sheet						Dynamic Balance sheet					
Variables (in %)	N	Min	Median	Max	Mean	StD	N	Min	Median	Max	Mean	StD
Realized losses												
Loan provisions / Total loans	178	-0.88	0.57	25.43	1.25	2.52	57	-0.41	1.01	7.20	1.56	1.70
(Bankscope)												
Exp. loss / Total loans	178	0.00	0.57	13.51	0.95	1.48	57	0.00	0.77	5.82	1.16	1.17
(Dec. 13 and Dec. 14)												
Loan provisions / Credit exposures	144	-0.44	0.20	3.54	0.41	0.61	46	-0.43	0.23	3.95	0.44	0.74
(EBA Transparency 15)												
Exp. loss / Credit exposures	144	0.00	0.27	2.41	0.41	0.41	46	0.00	0.26	3.32	0.38	0.52
(Dec. 14 and June 15)												
Macroeconomic releases												
Equity daily return	4802	-31.03	0.00	22.13	-0.01	2.29	1494	-33.33	0.00	50.00	0.21	6.85
$\triangle$Exp. loss / CET1	4802	-51.77	0.00	103.56	0.12	2.83	1494	-53.70	0.00	81.81	0.08	5.41

Table 4 Realized losses and ST model expected losses (Bankscope)

Regressions of bank loan loss provisions over total loans on stress test losses predictions with Eurostat macroeconomic data. *Exp. loss / Total loans* is defined as model prediction of credit losses over the loan portfolio of the bank.

	Loan provisions / Total loans				
			2013	2014	Dynamic BS
	(1)	(2)	(3)	(4)	(5)
Exp. loss / Total loans	0.334***	0.328***	0.313	0.347***	0.803***
	(0.126)	(0.126)	(0.219)	(0.108)	(0.165)
2013 year dummy		0.004			
		(0.004)			
Constant	0.009***	0.007**	0.012***	0.007***	0.006**
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
Adjusted R^2	0.03	0.04	0.01	0.10	0.29
Observations	178	178	89	89	57

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5 Realized losses and ST model expected losses (EBA transparency exercise)

Regressions of bank loan loss provisions over total credit exposure on stress test losses predictions with Eurostat macroeconomic data. *Exp. loss / Total credit exposure* is defined as model prediction of credit losses over total credit risk exposure of the bank.

	Loan provisions / Total credit exposure				
			Dec. 2014	June 2015	Dynamic BS
	(1)	(2)	(3)	(4)	(5)
Exp. loss / Total credit exp.	0.707***	0.690***	0.927***	0.323***	0.800***
	(0.111)	(0.106)	(0.171)	(0.095)	(0.177)
Dec. 2014 dummy		0.003***			
		(0.001)			
Constant	0.001*	-0.000	0.002*	0.001*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.22	0.29	0.29	0.13	0.30
Observations	144	144	72	72	46

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6 News shocks and stress test model predictions

Regressions of bank equity daily return on stress test model predictions at macroeconomic releases dates. △*Exp. losses / CET1* is the difference between the model loss prediction after a macroeconomic release and the model loss prediction with the economists' consensus from Bloomberg over common equity tier1 of the bank. Standard-errors are clustered at the bank level.

	Bank equity daily return						
					2013	2014	Dynamic BS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
△Exp. loss / CET1	-0.013***	-0.031***	-0.025***	-0.025***	-0.004	-0.050***	0.040
	(0.005)	(0.007)	(0.007)	(0.007)	(0.006)	(0.016)	(0.023)
Constant	-0.007	-0.005	-0.018	3.835***	3.868***	0.625***	0.334
	(0.036)	(0.035)	(0.166)	(0.544)	(0.464)	(0.217)	(0.313)
Adjusted R^2	0.00	0.23	0.24	0.24	0.19	0.30	0.12
Observations	4,802	4,802	4,802	4,802	2,401	2,401	1,494
Date FE	N	Y	Y	Y	Y	Y	Y
Country of origin FE	N	N	Y	N	N	N	N
Bank FE	N	N	N	Y	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$