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ABSTRACT

We provide a first evaluation of the quality of banking stress tests in the European Union. We use stress tests scenarios and banks' estimated losses to recover bank level exposures to macroeconomic factors. Once macro outcomes are realized, we predict banks' losses and compare them to actual losses. We find that stress tests are informative and unbiased on average. Model-based losses are good predictors of realized losses and of banks' equity returns around announcements of macroeconomic news. When we perform our tests for the Union as a whole, we do not detect biases in the construction of the scenarios, or in the estimated losses across banks of different sizes and ownership structures. There is, however, some evidence that exposures are underestimated in countries with ex-ante weaker banking systems. Our results have implications for the modeling of credit losses, quality controls of supervision, and the political economy of financial regulation.

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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. Stress testing exercises mobilize large human and financial resources among regulators and 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 comply with the guidelines and estimate their losses at a fairly granular level.

Yet, despite the clear importance of stress tests, their quality has not yet been formally tested. In fact, the data from the tests are typically used only once, to assess the health of the banks. Stress tests data, despite their richness and granularity, have not been used for further research. The issue, of course, is to figure out a way to use the data, since the scenarios of the stress tests (almost) 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 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 reliable information for regulators on the resilience of banks. 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 outcomes. These predicted loss rates can then be backtested using actual market and accounting data.

European 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 in all countries where they have significant exposures. 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 banks' sensitivity to macroeconomic shocks.

We obtain six main results. First, a simple logistic-linear model of bank loss rates fits the stress data well. Second, stress tests scenarios are not biased in favor of countries with ex-ante fragile banking systems. Third, model-estimated losses are unbiased predictors of realized losses across all the banks in our sample, and for small and large banks separately. Fourth, the 2011 stress tests did not have the same quality as the 2014 stress tests, consistent with the theoretical prediction of Faria e Castro et al. [2017] that a common backstop (however incomplete) allows regulators to perform more informative stress tests. Fifth, however, we find some evidence that estimated exposures are under-estimated in countries with ex-ante fragile banking sectors. Finally, we show that our estimated exposures predict the cross sectional variation of bank stock returns after macro announcements, which shows that market participants agree with our model's predictions (we cannot tell, however, if they learned the exposures from the stress tests themselves, or if they knew them all along).

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 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.

[1]The total assets of banks participating to the exercise represent almost 22 trillion.

Two macroeconomic scenarios are constructed for the 2014-2016 horizon: a baseline scenario, and an adverse scenario. Macroeconomic and financial variables (real 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.

Literature Review There is a growing theoretical literature on assets quality reviews. Goldstein and Sapra [2014] review the literature on the disclosure of stress tests results. Several recent papers study specifically the trade-offs involved in revealing information about banks' balance sheets. 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 [2015] study the reputation concerns of a regulator when there is a trade-off between moral hazard and runs. Faria e Castro et al. [2017] study a model of optimal disclosure where the government trades off Lemon market costs with bank run costs, and show that a fiscal backstop allows government to run more informative stress tests. Schuermann [2012] analyzes the design and governance (scenario design, models and projection, and disclosure) for more effective stress test exercises. In the prolongation, Schuermann [2016] particularly determines how wartime stress testing can be adapted to peacetime concerns in order to insure adequate lending capacity and other key financial services.

Most empirical papers on stress tests focus on the information content at the time of disclosure, using an event study methodology to determine whether stress tests provide valuable information to investors. Petrella and Resti [2013] assess the impact of the 2011 European stress test exercise. For the 51 banks with publicly traded equity, they find that the publication of the detailed results provided valuable information to market participants. Similarly, Donald et al. [2014] evaluate the 2009 U.S. stress test conducted on 19 bank holding companies and find significant abnormal stock returns for banks with capital shortfalls. Candelon and Sy [2015], Bird et al. [2015], and Fernandes et al. [2015] also find significant average cumulative abnormal returns for stress tested BHCs around many of the stress test disclosure dates. Flannery et al. [2016] find that U.S. stress tests contain significant new information about assessed BHCs. Using a sample of large banks with publicly traded equity, the authors find significant average abnormal returns around many of the stress test disclosures dates. They also find that stress tests provide relatively more information about riskier and more highly leveraged bank holding companies. Glasserman and Tangirala [2016] evaluate one aspect of the relevance of scenario choices. They show that the results of U.S. stress tests are somewhat predictable, in the sense that rankings according to projected stress losses in 2013 and 2014 are correlated. Similarly, the rankings across scenarios in a given year are also correlated. They argue that regulators should experiment with more diverse scenarios, so that it is not always the same banks that project the higher losses.

Our paper differs from the existing literature in that we attempt to directly evaluate the accuracy of the tests. Kovner and Philippon [2016] undertake the same exercise with U.S. CCAR data. CCAR and EBA stress tests share a common purpose but differ greatly in details, as discussed in Kovner and Philippon [2016]. For the purpose of this paper, the most important difference is the fact that EBA tests include one scenario per country, which gives us a lot more cross-sectional data to estimate and test the model.

1 Model

1.1 Estimating Loss Rates Sensitivity to Macroeconomic Factors

We want to use the data released during the stress tests to estimate banks' exposures to macroeconomic shocks. 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.[2] Banks report 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 scenario. The units of observation in our model are therefore:

- name of the bank $i \in [1:122]$
- scenario $s \in \{\text{baseline, adverse}\}$ and projection year $t = \{2014, 2015, 2016\}$
- country of operation $j \in [1:28]$
- portfolio $p \in \{\text{retail, corporate}\}$

We can define a scenario as follows

Definition 1. A **scenario** s is a sequence of vectors representing the macroeconomic factors in country j at time t.

In our application, we will use the macro-variables $g^s_{j,t}$, $\pi^s_{j,t}$ and $\Delta u^s_{j,t}$, where g is the growth rate of real GDP, π the inflation rate, and Δu the change in the unemployment rate, in country j at time t under scenario s. Given the correlation between these macroeconomic variables, we assume that banks are exposed to a one-dimensional factor which is a linear combination of the

[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.

three macroeconomic variables:

$$y_{j,t}^{s} = \begin{bmatrix} c_1^{g} & c_1^{\pi} & c_1^{\Delta u} \end{bmatrix} \cdot \begin{bmatrix} g_{j,t}^{s} \\ \pi_{j,t}^{s} \\ \Delta u_{j,t}^{s} \end{bmatrix}$$

where c_1^{g}, c_1^{π} and $c_1^{\Delta u}$ are the factors' loading of the first component in a principal component analysis on $g_{j,t}^{s}$, $\pi_{j,t}^{s}$ and $\Delta u_{j,t}^{s}$. We have also estimated a model with only growth and inflation and the results are essentially unchanged, with slightly larger standard errors.

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

The majority of banks included in the stress test have branches or subsidiaries in several countries so we have several exposures per bank. Finally, a model is a mapping from scenarios to loss rates

Definition 3. A **model** of portfolio losses is a mapping from scenarios $y_{j,t}^{s}$ to results $l_{i,j,t}^{s,p}$

$$l_{i,j,t}^{s,p} = F_{p,i,j}\left(y_{j,t}^{s}\right)$$

It is clear that different portfolios (retail, corporate) have different sensitivities to macroeconomic factors, so the mapping needs to 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 Italian GDP. On the other hand, if we do not restrict the model, we would potentially end up with 28 (countries of exposure) $\times 122$ (banks) $= 3,416$ degrees of freedom. We therefore estimate the following specification for losses on portfolio p:

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

We allow for bank fixed effects. The macro-sensitivity has two components. The 28 country-specific θ^p_j capture differences in legal systems, recovery rates, extent of recourse, collateral repossession, etc. The 122 bank-specific β^p_i capture systematic differences in risk management across banks, among other characteristics.

1.2 Using the Model to Predict Actual Outcomes

The second step of our analysis is to use the estimated model to predict actual outcomes. We consider two sets of outcomes: realized losses and stock returns.

1.2.1 Realized Losses

Let $Y_t \equiv \{y_{j,t}\}_{j=1..28}$ be the actual realization of the global factor of macro variables. The key idea of our backtesting exercise is to use Y to predict actual losses. 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. We therefore aggregate our predictions from equation (1) up to the bank/portfolio level:

$$\mathbb{E}\left[L^p_{i,t} \mid Y_t\right] = \sum_{j=1}^{28} \frac{\exp\left(\hat{\alpha}^p_i + \hat{\beta}^p_i \hat{\theta}^p_j \cdot y_{j,t}\right)}{1 + \exp\left(\hat{\alpha}^p_i + \hat{\beta}^p_i \hat{\theta}^p_j \cdot y_{j,t}\right)} \times EXP^p_{i,j} \tag{2}$$

where $EXP_{i,j}$ is the outstanding exposure of bank i to country j.[3] $\mathbb{E}\left[L_{i,t} \mid Y_t\right]$ is then equal to $\mathbb{E}\left[L_{i,t}^{corp} \mid Y_t\right] + \mathbb{E}\left[L_{i,t}^{retail} \mid Y_t\right]$. These predictions can then be backtested against realized losses by running the following regression:

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

where $L_{i,t}$ are the realized losses of bank i.

1.2.2 Macro News and Stock Returns

Comparing our predictions to realized losses is the most natural way to assess the reliability of the stress test, but this approach suffers from limited statistical power: we have to wait for the macro scenario to materialize and then we only get one observation per bank.

To overcome this limitation, 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

$$\Delta_\tau \mathbb{E}\left[L_{i,\tau}\right] = \sum_{j=1}^{28} \left(\frac{\exp\left(\hat{\alpha}_i^p + \hat{\beta}_i^p \hat{\theta}_j^p \cdot y_{j,\tau^+}\right)}{1 + \exp\left(\hat{\alpha}_i^p + \hat{\beta}_i^p \hat{\theta}_j^p \cdot y_{j,\tau^+}\right)} - \frac{\exp\left(\hat{\alpha}_i^p + \hat{\beta}_i^p \hat{\theta}_j^p \cdot y_{j,\tau^-}\right)}{1 + \exp\left(\hat{\alpha}_i^p + \hat{\beta}_i^p \hat{\theta}_j^p \cdot y_{j,\tau^-}\right)} \right) \times EXP_{i,j} \tag{4}$$

[3] Because the model is non-linear, we need to correct a potential bias due to Jensen's inequality. Since the bias depends on the properties of the error term in (2), we proceed as follows. First, we regress the stress test loss rates on the same right hand side factors in equation (1) and obtain the fitted values. Second, we regress the log of the odd ratio exactly as in (1). We obtain the fitted values and compute the fitted loss rates with the inverse logit function. Finally, we regress the former fitted loss rates on the latter. The coefficient of this last regression gives us an estimate of the bias due to non-linearity. Note that this approach is designed in such a way that the coefficient is exactly one if we test the model in sample, i.e., in the stress test data. We find a relatively small bias of 1.06. We adjust accordingly all model predictions in the paper by multiplying them by 1.06.

The predicted losses can then be compared to the excess return of bank i at time τ:

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

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

2 Data

We gather four sets of data: the EU 2014 stress test results, accounting data on realized losses, macroeconomic news, and equity returns. In the last section of the paper, we also study the 2011 stress tests.

2.1 Stress Test Data

Our main data set consists of the publicly disclosed European stress test results on 123 European banks.[4] One bank did not have any material exposure to retail and corporate customers and is thus not included in our framework. 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.

We focus our analysis on corporate and retail portfolios which represent by far the largest share of bank credit activities. Each bank breaks down its credit exposures up to the 10 countries of exposure in its banking book. For each country of exposure we have information on bank loss rate in years 2014, 2015 and 2016 under two scenarios defined by the EBA: a baseline scenario – which reflects the expected macroeconomic conditions to be realized 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. For bank i in country j we therefore have 6

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

predicted loss rates for the retail portfolio, and 6 for the corporate portfolio.

The stress test was carried out under a general principle of static balance sheets, assuming no asset growth over the 3 years horizon of the test and that maturing assets are replaced with similar exposures in terms of credit quality and maturity. No replacement or write-down of defaulted assets was allowed. Some banks, however, had a restructuring plan approved by the European commission before December 2013. These 32 banks 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 for the troubled assets they were supposed to cut-off under the restructuring plans. We therefore exclude them from our backtesting analysis.

Table 1 presents summary statistics for the scenarios and for the credit loss rates. The baseline scenario has a positive average growth of 1.92%, and a slight decrease of 0.30 p.p. in the unemployment rate. In the adverse scenario, real GDP growth is negative -0.92% and the unemployment rate increases by 0.79 p.p. Inflation is 1.56% in the baseline and 0.49% in the adverse scenario. As expected, loss rates are much higher in the adverse scenario. The median loss rate is 0.33% in the baseline scenario and 0.60% in the adverse scenario, while the mean loss rates are 0.59% and 1.00%, respectively.

2.2 Macroeconomic Data

We use two types of macro data: realized series, and announcements. To predict credit losses, we collect harmonized macroeconomic series for EU countries for 2013, 2014 and 2015 from S&P Global Market Intelligence.

Data on macroeconomic news – which we define as announcements above or below consensus – are from Bloomberg. We collect the date, country, nature of the macroeconomic announcement and the consensus forecast (which is the median of a panel of economists' forecast). We find 2,148 announcements about GDP growth, inflation and unemployment rates in 2013 and 2014. We compute the macroeconomic surprise as the difference between the actual published figure and the forecast. We then eliminate the observations where there is no surprise (actual equals consensus) or where the consensus is not available. Our final set of announcements contains 949 macroeconomic surprises.

2.3 Bank Level Data

We collect the end of year loan loss provisions and total loans in 2013, 2014 and 2015 from Bankscope, which covers 92 banks from the stress test exercise. Finally, we collect equity returns for the 45 listed banks from Bloomberg. We compute the daily return on each announcement date in our sample (described above).

3 Results

3.1 Estimation of the Model

We start with the principal component analysis to obtain the scalar macro factor y. Table 2 shows the three principal components with their respective loadings for each variable, their eigenvalue and proportion of variance explained. As one can expect, the first component loads positively on real GDP growth and inflation rates and negatively on change in unemployment rate. It is the only component with an eigenvalue greater than 1. We use the factor loadings of this first principal component to compute $y^s_{j,t}$.[5]

We then estimate the model in equation (1) using the stress test results. We have 3,148 loss rates observations for the corporate portfolio and 2,760 observations for the retail portfolio. We estimate the parameters in two steps. First, we set $\beta_i = 1$ and we estimate 28 θ^p_j parameters for the corporate portfolio and 28 θ^p_j parameters for the retail portfolio, together with the fixed effects α^p_i.

[5]To check the robustness of our results, we tested alternative specifications for $y^s_{j,t}$ using the first two principal components, the two macroeconomic factors g and π and the three macroeconomic factors g, π and u. Overall, our results remain consistent. Tables with these alternative specifications are in the Appendix.

Table 3 describes the estimation. Table 4 present our estimated country-of-exposure sensitivities $\hat{\theta}_j$, with θ_{France} normalized to one. All coefficients are positive, except for Hungary and Greece (for the retail portfolio). Sensitivities are fairly similar among the large countries: Germany has 0.9 and Italy 0.84 for the corporate portfolio and 0.72 for the retail portfolio. The United Kingdom, with coefficients of 0.56 for the corporate portfolio and 0.53 for the retail portfolio, seems to have a lower elasticity to a global shock than France. As a robustness check, we use a constrained model in which we impose $\theta_j > 0.5$. The results are similar and reported in the Appendix.

In the second step, we fix $\hat{\theta}_j^p$ and we estimate 122 bank-specific β_i^p parameters for the corporate portfolio, and 117 β_i^p for the retail portfolio, together with fixed effects α_i^p. Table 3 shows that the model explains about half of the sample variance. Table 4 presents summary statistics about bank sensitivities $\hat{\beta}_i$. The mean is -0.44. Recall that the principal component has a loading on growth of 0.64, so if growth is 1% lower in France, the loss rate on portfolios of French credit is 28 basis points higher. There is, however, a fair amount of dispersion: the standard deviations are 0.22 and 0.27 for corporate and retail exposures, respectively. Table 4 also presents the weighted average of $\hat{\beta}_i$ by country-of-origin. The weights are given by banks' credit exposure. In the robustness check with $\theta_j > 0.5$ we also impose $\beta_i < -0.2$. Our main results are robust to this choice and are reported in the Appendix.

3.2 Are Stress Test Scenarios Biased?

There are two potential biases in a stress test exercise. There could be a bias in the design of the scenarios, or there could be a bias in the exposures reported by the banks. Given that scenarios are public, investors can in principle reevaluate stress test results with more severe scenarios if they wish. In practice, however, this is not necessarily straightforward. In fact, they would need to estimate banks' sensitivity just as we do, and then input an alternative scenario.[6]

[6]For the same reason, the existence of a scenario bias is not a direct challenge to our approach as we focus on estimating banks' sensitivity to macroeconomic shocks. As long as the baseline and adverse scenarios differ enough, we should be able to estimate our parameters.

Before turning to our main backtesting exercise, it is therefore useful to take a closer look at the scenarios. Table 5 presents the baseline forecast error, i.e., the realizations in 2014 and 2015 minus the baseline scenario. The baseline scenarios seem a bit pessimistic. Real GDP growth turn out higher than predicted by 0.24% and unemployment rate lower by -0.48%. Inflation rate on the other hand is -1.22% below the baseline. Forecasters underestimated the risk of deflation, which is not altogether surprising given the ex-post commodity price shocks and the longer than expected ZLB episode.

Next we test for biases *across* countries. Given that banking sector strength varies in the European Union, one could worry about more lenient scenarios for countries with weaker banking sectors. Table 6 shows that this is not the case. We define banking sector *ex ante* weakness as the average credit loss rates of the country under the baseline scenario for the corporate ($loss_j^{base,corp}$) and retail ($loss_j^{base,retail}$) portfolios. These variables are mostly uncorrelated with the baseline forecast error. The only significant correlation – between $loss_j^{base,corp}$ and the baseline forecast error for GDP growth – is actually positive (+0.27), so countries with weaker banking system has more (not less) pessimistic baseline scenarios.

Finally, we can check the severity of the adverse scenario. The adverse scenario is not a forecast, but it is an important choice for the regulators. We define scenario severity as the difference between baseline and adverse scenarios for g and π and the difference between adverse and baseline scenarios for u, so that a higher number indicates a more severe adverse scenario. Scenario severity for g and π is not correlated with banking system fragility. Scenario severity for u is negatively correlated with banking system fragility, but this is of course what any model of mean reversion would predict, and we have already seen that the baseline was, if anything, pessimistic for weak countries. Figure 1 shows that among Greece, Italy, Ireland, Portugal and Spain, only Greece has a higher realized unemployment rate than the baseline scenario, and by a small amount.

We conclude, that there is no evidence of bias in the design of macro scenarios.

3.3 Descriptive Statistics

Table 7 presents descriptive statistics on realized losses and returns, together with the model's predictions. Bankscope data covers the end-of-year results for 2013, 2014 and 2015. The median expected losses in the model are close to the median of realized losses in the sample of banks. Realized losses are more skewed than model-implied losses, so we miss the max and the mean. The average and median realized equity returns are essentially zero, but with significant cross-sectional dispersion that our model will seek to explain.

3.4 Predicted vs. Realized Losses

We start our backtesting exercise by comparing predicted and realized losses. We use realized macroeconomic figures to predict accounting losses on a yearly basis using equation (2). We compare the predictions with loan loss provisions reported by banks in their profit and loss accounts. Loss predictions are normalized by bank's credit exposure as reported in the stress test data and accounting loan loss provisions are normalized by bank loan portfolio at the end of the corresponding year from Bankscope.

Table 8 shows that the model explain realized losses fairly well. As a benchmark, Column (1) shows that baseline losses predict actual losses with a coefficient close to one and an R^2 of 0.29. We can now ask whether our model brings in additional information relative to these baseline projections. Columns (2), (3) and (4) show that our model's predictions improve the fit and render the baseline insignificant. Column (5), (6) and (7) show that our model explain a large share of the deviation of realized losses from the baseline. In 2014, our model can predict 43% of the deviations from the baseline. In 2015, our model explains 21% of the deviation with a coefficient very close to one.

Our results show that stress tests provide useful information about banks' exposures, and the coefficient are close to one, as one would predict if the tests are unbiased.

One drawback of using realized losses is that we have to wait for the data to come in and we have a relatively small sample. As an additional test, we propose in the next section to compare market reactions to the change in expected losses based on the announcement of macro news.

3.5 Macro News and Equity Returns

Table 9 compares the change in predicted losses obtained from equation (4) with equity returns on the day of macroeconomic announcements. The change in expected loss is the difference between the expected loss after the macroeconomic release and the expected loss under the last economists' consensus provided by Bloomberg. Our sample includes only 45 listed banks, but many announcements.

Columns (1) of Table 9 shows that changes in expected losses predicted from the model are indeed negatively correlated with banks' equity returns, controlling for the Eurostoxx 600 market return. The coefficient is significant at the 1% level. The effect seems also economically significant as an increase in 1 p.p of expected losses over CET1 leads on average to an equity return decrease of -0.3 p.p. As an alternative to the market return, column (2) to (4) include event-date fixed effects. The results show that our estimated model can predict the cross-section of equity returns. Columns (4) and (5) show that country of origin and bank fixed effects do not affect our results.

These results show that stress tests are informative and that market participants use a pricing model that is consistent with the one that we propose. At this point, we do not have a way to know whether markets learn from the stress tests or whether they simply agree with the results.

4 Additional Market-Based Evidence of Informativeness

In the previous section we used an event study approach based on macro news to test the prediction of the model. This allowed us to increased the number of observations from about 180 to about 5,000. We now explain how we can increase the number of observations by using all daily returns, and not only the ones linked to releases of macroeconomic news. The idea is to create a bank-specific market factor using our estimated banks' exposures and the daily returns on broad stock indexes in the 28 countries of exposures.

Stress test results allow us to estimate bank vulnerability by country of exposure. An additional way to test our model is then to compute a bank-specific factor using market indexes weighted by the bank-specific sensitivity to macroeconomic shocks. The advantage of this approach is that we can use all daily market returns, which brings the number of observations to about 23,000.

The question then is how to estimate the market specific factor. We have done it in two ways, first using our previous estimates of macro-elasticities. The other way, which we report below, is simpler and we find it particularly useful because it is a non-parametric test of the stress-test data. It does not rely on our estimation of the elasticities or on the functional form of equation (1). To save space we only report the non-parametric results. The results using estimated elasticities are similar and available upon request.

Our non-parametric bank-country exposure $\bar{\beta}_{i,j}$ is simply the relative losses in the adverse and baseline scenarios, normalized average of all banks for the same country of exposure:

$$\bar{\beta}_{i,j} = \frac{\sum_{t=1}^{3} \frac{L_{i,j,t}^{adverse}}{L_{i,j,t}^{baseline}}}{\sum_{t=1}^{3} \frac{\sum_i L_{i,j,t}^{adverse}}{\sum_i L_{i,j,t}^{baseline}}} \tag{6}$$

where L is the amount of losses of bank i in country j in year t under the corresponding scenario. The stress test market factor can then be computed as a weighted average of country market equity returns:

$$F_{i,\tau}^{ST} = \frac{\sum_{j=1}^{28} \bar{\beta}_{i,j} \times EXP_{i,j} \times r_{j\tau}^{m}}{\sum_{j=1}^{28} \bar{\beta}_{i,j} \times EXP_{i,j}} \tag{7}$$

where r_j^m is a domestic market return and EXP is the credit exposure. To test the information content of all the elements of the stress test, we also construct a factor using only the exposures (setting all β's to one), which we call the simple exposure-weighted factor.

Table 10 compares our stress test market factors to other market factors using daily returns in 2013 and 2014. We use a broad index (Eurostoxx 600), the simple exposure-weighted factor, and the sensitivity-exposure-weighted factor from equation (7). Column (2) shows that using exposures weights double the R^2. Column (3) shows that our stress test market factor has a higher coefficient and a smaller standard error than other factors. Columns (4) to (6) show that the sensitivity-weighted factor renders the other factors insignificant and is robust to fixed effects.

This robustness exercise confirms, using a different methodology, that the stress test contains valuable information on banks' sensitivity to shocks. The information goes beyond the simple exposure of a bank to a particular country. For a given exposure, the stress tests seems to correctly identify the relative sensitivities of banks.

5 Heterogeneity in Model Prediction Accuracy

So far, we have shown that, across our entire sample, stress test results contain accurate information about banks' exposures. This does not mean, however, that there is no bias for a subset of banks. This is what we now test.

To explore the heterogeneity in model prediction accuracy, we rank the deviation between realized and predicted losses according to three dimensions: bank size, government ownership and country of origin. Table 11 shows the results of our benchmarking exercise. We compute the model bias as the difference between loan loss provisions over total loans and the model loss predictions over total exposures *minus* the mean deviation in the sample of banks.

- Bank Size

Bank size is much discussed in the literature. Models of regulatory capture, for instance, emphasize that large banks can exert more influence on their regulators. At a more technical level, larger banks are more likely to rely on internal models. We use two measures of size: absolute, and relative to the country.

We first sort banks into deciles based on their total assets (from Bankscope). The first column of Panel A of Table 11 shows the model bias by decile for 2014 and 2015. We do not observe any systematic bias according to bank size: only the eighth decile shows some significance but the bias is actually negative, i.e. realized losses are lower than predicted losses compared to the rest of the sample. We also test for the effect of relative size by classifying banks into size decile based on their total assets over their country of origin's GDP. Results reported in the Appendix show again that model biases are not linked to bank size.

- Government Ownership

Government ownership is an information directly available in the stress test data. There are 9 government-owned banks that we can match with Bankscope data. Panel B of Table 11 shows the model bias for both groups. Again, we find no bias. If anything, we find that banks controlled by government have a conservative bias.

- Country of Origin:

Finally, Panel C of Table 11 presents results by country of origin. Here the amplitude of the deviation between countries is much greater, and we find some evidence of biases, in the case of Italy, and to a lesser extent, Spain.[7]

Given these results, we then ask if there is a connection between the weakness of the banking sector and the bias in the stress test results. Table 12 reports the correlation between prediction errors, scenarios, and banking sector *ex ante* fragility. The results again show that the scenarios are not biased. There is no correlation between the deviation of GDP growth from the baseline and the prediction errors of the model. Note that this is a very useful test of the functional form that we have chosen because it shows that the biases are not driven by negative (or positive) macroeconomic outcomes. There is some correlation between unemployment rate errors and model

[7] Finland, Hungary, Ireland, Latvia, Malta, Norway and Portugal have only one bank represented in our sample.

errors but it is negative so the model over-predict losses when unemployment turns out higher than expected. So if anything we might have a bit too much non-linearity in our model. In any case, GDP growth is the most important predictor in practice.

We do find, however, that model bias is positively correlated with banking sector *ex ante* fragility. Thus, banks headquartered in a country with a fragile banking sector have on average higher losses than predicted losses, relative to other banks. It appears that stress test loss estimates were somewhat lenient in countries with weaker banking system. The correlation is not very high, and the bias is not overwhelming, but it is statistically significant.

6 Backtesting the 2011 Stress Tests

Our last task is to compare the 2011 and 2014 stress tests exercises. The 2011 exercise was conducted by the EBA, 21 national supervisory authorities (NSAs), the ECB and the European Commission. The quality assurance was led by the national supervisory authorities (NSAs) and the EBA based on historical experience, assessment against peers and against top-down benchmarks. The main difference between 2011 and 2014 was the degree of involvement and quality control by the ECB, and the fact that by 2014 Europe had put in place some backstops to be able to stabilize a country's banking system if needed. These backstops are still incomplete, but represent a dramatic improvement compared to what existed in 2011.

The 2011 tests covered 90 banks representing 65% of the European banking system, and least 50% of each national banking sectors measured by total consolidated assets. The tests provided significant information about sovereign exposures. The results were published on July 15 2011. Twenty banks fell below the 5% Core Tier 1 Ratio threshold over the two-year horizon of the exercise. The shortfall amounted to EUR 26.8 bn.

We backtest the 2011 exercise using the same methodology as before, except that the published results are less granular than during the 2014 exercise. The data on loss rates were only available on consolidated basis. Therefore, the estimations of the loss rates sensitivity to the macroeconomic factors are realized on 3 units of observation namely bank i, scenario s and portfolio p.

The results in Table 13 are markedly different from the ones obtained earlier. We find that the predictive power is weaker, and that most of it comes from the baseline scenario (Table 13, columns 1, 2, 3, and 4), which itself appears too optimistic (coefficient significantly larger than one). Deviations from the baseline are not well explained by the model.

We draw three conclusions from this comparison. First, our model is able to tell the difference between a high quality test and a low quality test. Second, the quality of EU stress tests has improved over time. Third, these results are consistent with the prediction of Faria e Castro et al. [2017] that centralized supervision and joint backstops is more likely to provide accurate disclosure of information.

7 Conclusion

We provide the first independent assessment of the quality of stress tests in Europe. We obtain two main sets of results. First, we show that a (relatively) simple statistical framework can provide an accurate description of stress test data, and fairly efficient predictions of realized losses. Moreover, market participants appear to share this view.

Second, we shed some light on the political economy of stress testing. Contrary to common wisdom, we do not find any bias in the design of the scenarios, or in favor of large banks and government-owned banks. We do, however, find some evidence of relatively more lenient exposures' estimates in countries with relatively weaker banking sectors, consistent with models of forbearance driven by either macroeconomic risks or reputation concerns. We also document a significant quality improvement between the 2011 and 2014 tests. Overall, our findings support the view of Faria e Castro et al. [2017] that centralized banking supervision is more likely to be accurate and unbiased.

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Table 1: Descriptive Statistics of EBA 2014 Stress Test Exercise

Summary of stress test results and scenarios input for credit risk. *Loss rate* is the flow of new losses over credit exposure for the retail and corporate portfolios. The scenarios are displayed for 2014, 2015 and 2016. g is the real GDP growth rate under the EBA scenario. *pi* is the price inflation under the EBA scenario. u is the unemployment rate under the EBA scenario. Δu is the change in unemployment rate.

	Loss rate		g		π		u		Δu	
	baseline	adverse	baseline	adverse	baseline	adverse	baseline	adverse	baseline	adverse
N	2,954	2,954	84	84	84	84	84	84	84	84
Min (%)	0.00	0.00	-4.80	-6.30	-0.60	-2.50	4.70	5.00	-4.50	-3.70
Median (%)	0.33	0.60	1.80	-0.80	1.60	0.70	9.45	11.55	-0.20	0.75
Max (%)	7.45	8.87	4.30	2.10	3.40	2.50	26.00	27.10	3.30	3.70
Mean (%)	0.59	1.00	1.92	-0.92	1.56	0.49	10.64	12.64	-0.30	0.79
StD (%)	0.76	1.20	1.16	1.40	0.64	1.05	5.09	5.26	0.83	1.06

Table 2: PCA of Stress Test Scenarios

This table presents the principal component analysis of the macroeconomic stress test scenarios for real gdp growth (g), inflation rate (π) and the change in unemployment rate (Δu).

	1^{st} component	2^{nd} component	3^{rd} component
g loading	0.64	-0.18	0.74
π loading	0.48	0.86	-0.20
Δu loading	-0.60	0.49	0.64
Eigenvalue	1.88	0.76	0.35
Prop. variance (%)	62.75	25.50	11.76
Observations	168		

Table 3: Summary of Model Estimation

Summary output of the model in equation (1). The model is estimated in two steps. For the first step, θ_j^p parameters are obtained by setting $\beta_i = 1$. For the second step, we use $\hat{\theta}_j^p \cdot y_{t,j}^s$ from the first step to estimate the β_i parameters of the model. The table shows which parameters are included in each step and the respective R^2.

	$\ln \frac{loss\ rate}{1-loss\ rate}$			
	1^{st} step of model		2^{nd} step of model	
	Setting $\beta_i = 1$		Using $\hat{\theta}_j^p \cdot y_{t,j}^s$ from step 1	
	Corporate	Retail	Corporate	Retail
	(1)	(2)	(3)	(4)
# of α parameters	122	117	122	117
# of θ parameters	28	28		
# of β parameters			122	117
R^2 (%)	53.07	48.23	54.31	49.63
Observations	3,148	2,760	3,148	2,760

Table 4: Distribution of Parameters

Distribution of country sensitivity $\hat{\theta}_j$, $\hat{\beta}_i$ and weighted average $\hat{\beta}_i$ parameters by banks' country of origin. Weights are given by banks' credit exposure. All parameters are normalized by $\hat{\theta}_{FRANCE}$.

	$\hat{\theta}_j$			$\hat{\beta}_i$ (weighted average)	
	Corporate	Retail		Corporate	Retail
Austria	1.28	0.31		-0.36	-0.41
Belgium	0.67	0.80		-0.30	-0.58
Bulgaria	0.70	0.52			
Croatia	0.77	0.50			
Cyprus	0.15	0.19		-0.44	-1.01
Czech Republic	0.41	0.70			
Denmark	0.95	0.85		-0.43	-0.61
Estonia	0.98	1.09			
Finland	0.68	0.61		-0.90	-0.84
France	1	1		-0.53	-0.42
Germany	0.90	0.90		-0.40	-0.27
Greece	0.28	-0.29		-0.87	-0.55
Hungary	-0.14	-0.82		-0.30	-0.19
Ireland	0.32	0.37		-0.69	-0.48
Italy	0.84	0.72		-0.44	-0.41
Latvia	0.72	0.55		-0.20	-0.40
Lithuania	0.66	0.43			
Luxembourg	0.86	1.48		-0.30	-0.43
Malta	0.38	1.85		-0.51	-0.42
Netherlands	0.90	0.60		-0.45	-0.37
Poland	0.56	0.38		-0.45	-0.50
Portugal	0.52	0.55		-0.50	-0.66
Romania	0.18	0.51			
Slovakia	0.72	0.52			
Slovenia	0.38	0.45		-0.24	-0.43
Spain	0.55	0.77		-0.46	-0.40
Sweden	0.39	0.25		-0.46	-0.34
United Kingdom	0.56	0.53		-0.58	-0.32

Distribution of $\hat{\beta}_i$	Min	Median	Max	Mean	StD

Corporate (N = 122)	-1.25	-0.43	0.05	-0.44	0.22
Retail (N = 117)	-1.46	-0.44	0.44	-0.44	0.27

Table 5: Comparison Baseline Scenarios and Realized

Deviation between realized macroeconomic figures and stress test baseline scenarios in 2014 and 2015.

Deviation between realized and baseline scenarios	g	π	u
N	56	56	56
Min (%)	-3.23	-4.00	-4.07
Median (%)	0.24	-1.22	-0.48
Max (%)	4.93	-0.33	2.15
Mean (%)	0.36	-1.38	0.52
StD (%)	1.53	0.83	1.36

Table 6: Banking System Fragility and Scenario Bias

Correlation matrices between banking system *ex ante* fragility and scenario bias. Banking system *ex ante* fragility is proxied by the country average baseline loss rate for the corporate ($loss_j^{base,corp}$) and retail portfolios ($loss_j^{base,retail}$). g^{real}, π^{real} and u^{real} are, respectively, the *realized* real GDP growth, inflation and unemployment rates in 2014 and 2015. g^{base}, π^{base} and u^{base} are, respectively, the real GDP growth, inflation and unemployment rates in the stress test *baseline* scenario. g^{adv}, π^{adv} and u^{adv} are, respectively, the real GDP growth, inflation and unemployment rates in the stress test *adverse* scenario.

A) Real GDP Growth Rate

	$\text{g}^{real} - \text{g}^{base}$	$\text{g}^{real} - \text{g}^{adv}$	g^{adv}	$\text{g}^{base} - \text{g}^{adv}$	$\text{loss}_j^{base,corp}$
$\text{g}^{real} - \text{g}^{base}$	1				
$\text{g}^{real} - \text{g}^{adv}$	0.67*	1			
g^{adv}	-0.01	-0.38*	1		
$\text{g}^{base} - \text{g}^{adv}$	-0.23	0.57*	-0.66*	1	
$\text{loss}_j^{base,corp}$	0.27*	0.24	-0.23*	0.07	1
$\text{loss}_j^{base,retail}$	0.13	0.01	-0.12	-0.00	0.70*

B) Inflation Rate

	$\pi^{real} - \pi^{base}$	$\pi^{real} - \pi^{adv}$	π^{adv}	$\pi^{base} - \pi^{adv}$	$\text{loss}_j^{base,corp}$
$\pi^{real} - \pi^{base}$	1				
$\pi^{real} - \pi^{adv}$	0.58*	1			
π^{adv}	-0.06	-0.65*	1		
$\pi^{base} - \pi^{adv}$	-0.38*	0.53*	-0.82*	1	
$\text{loss}_j^{base,corp}$	-0.22	-0.24	-0.08	-0.04	1
$\text{loss}_j^{base,retail}$	-0.23	-0.26*	-0.11	-0.05	0.70*

C) Unemployment Rate

	$\text{u}^{real} - \text{u}^{base}$	$\text{u}^{real} - \text{u}^{adv}$	u^{adv}	$\text{u}^{adv} - \text{u}^{base}$	$\text{loss}_j^{base,corp}$
$\text{u}^{real} - \text{u}^{base}$	1				
$\text{u}^{real} - \text{u}^{adv}$	0.75*	1			
u^{adv}	-0.26*	-0.28*	1		
$\text{u}^{adv} - \text{u}^{base}$	-0.06	-0.71*	0.26*	1	
$\text{loss}_j^{base,corp}$	-0.15	0.03	0.39*	-0.24*	1
$\text{loss}_j^{base,retail}$	-0.18	0.02	0.39*	-0.23*	0.70*

* $p < 0.05$

Table 7: Descriptive Statistics

Provisions / Loans is the ratio of loan loss provisions over total loans from Bankscope in december 2013, 2014 and 2015. *Exp. losses / Exposure* is the model prediction of loan losses with realized macroeconomic figures for real GDP growth, inflation and unemployment rates in 2013, 2014 and 2015 over bank's credit exposure in the 2014 stress test exercise. *Equity return* is the daily equity return. $\triangle$*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.

	Realized losses		Macro News	
		Model		Model
	$\frac{Provisions}{Loans}$	$\frac{Exp.loss}{Exposure}$	Equity return	$\frac{\triangle Exp.loss}{CET1}$
N	272	272	5,079	5,079
Min (%)	-0.88	0.03	-31.03	-3.30
Median (%)	0.52	0.49	0.00	0.00
Max (%)	25.43	5.13	22.13	8.14
Mean (%)	1.15	0.75	0.00	0.02
StD (%)	2.37	0.76	2.27	0.30

Table 8: Deviations from Baseline Predictions

Regressions of bank loan loss provisions over total loans on stress test losses predictions with realized macroeconomic data in 2014 and 2015. *Exp. loss / Exposure* is defined as model prediction of credit losses over bank's credit exposure. *Baseline ST losses / Exposure* is the loan losses under the stress test baseline scenario in 2014 and 2015 as published by the European Banking Authority (EBA) over bank's credit exposure.

	Provisions / Loans				$\frac{Provisions}{Loans} - \frac{Baseline\ ST\ loss}{Exposure}$		
			2014	2015		2014	2015
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline ST loss / Exposure	0.982***	-0.017	-0.134	0.160			
	(0.115)	(0.127)	(0.161)	(0.192)			
Exp. loss / Exposure		1.452***	1.773***	1.014***			
		(0.132)	(0.165)	(0.202)			
(Exp. - Baseline ST loss) / Exposure					1.206***	1.427***	0.910***
					(0.126)	(0.171)	(0.183)
Constant	0.001	-0.002	-0.002	-0.000	0.001	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year dummy	Y	Y			Y		
Adjusted R^2	0.29	0.58	0.69	0.43	0.34	0.43	0.21
Observations	180	180	91	89	180	91	89

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

Table 9: Macro News and Equity Returns

Regressions of bank equity daily return on stress test model predictions at macroeconomic releases dates. $\triangle$*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. *Market return* is the return of the Eurostoxx 600. Standard-errors are clustered at the bank level.

	Bank equity daily return			
	(1)	(2)	(3)	(4)
$\triangle$Exp. loss / CET1	-0.299***	-0.254***	-0.250***	-0.256***
	(0.060)	(0.074)	(0.068)	(0.070)
Market return	1.143***			
	(0.097)			
Constant	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.16	0.24	0.25	0.24
Observations	5,079	5,079	5,079	5,079
Date FE	N	Y	Y	Y
Country of origin FE	N	N	Y	N
Bank FE	N	N	N	Y

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

Table 10: Model-Weighted Market Factor and Equity Returns

Regressions of bank equity daily return on a market factors, exposure weighted market factor and stress test weighted market factor. *European market return* is the return of the Eurostoxx 600. *Exposure market factor* is the average of country market indices return weighted by country exposure size. *Stress test market factor* is the average of country market indices return weighted by country exposure size times the $\bar{\beta}_{i,j}$ sensitivity to the adverse scenario. $\bar{\beta}_{i,j}$ is defined in equation (6). Standard-errors are clustered at the bank level.

	Bank equity daily return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
European market factor	1.162***						
	(0.078)						
Exposure market factor		1.193***		-0.365	-0.328	-0.317	-0.318
		(0.084)		(0.430)	(0.422)	(0.412)	(0.412)
Stress test market factor			1.281***	1.659***	1.593***	1.580***	1.581***
			(0.056)	(0.441)	(0.436)	(0.425)	(0.426)
Constant	0.000	0.000	0.000	0.000	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.15	0.30	0.32	0.32	0.35	0.35	0.35
Observations	22,294	22,294	22,294	22,294	22,294	22,294	22,294
Date FE	N	N	N	N	Y	Y	Y
Country of origin FE	N	N	N	N	N	Y	N
Bank FE	N	N	N	N	N	N	Y

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

Table 11: Heterogeneity in Model Prediction

Comparison of realized loss rates vs. predicted loss rates based on different classification criteria. *Model Bias* is the difference between loan loss provisions over total loans and model losses predictions over credit exposure *minus* the mean error for the whole sample of banks. *Bank Size* ranks banks by total assets' deciles. *Government* is a dummy variable indicating if a bank is controlled by the government or not. *Bank country of origin* computes model bias by country of origin. Countries with only one bank are not reported.

A) Bank Size

Decile	Model Bias (%)	Model Bias 2014 (%)	Model Bias 2015 (%)
1 (small)	-0.07	-0.02	-0.21
2	-0.28	-0.00	-0.24
3	0.60	0.35	0.64
4	0.25	0.20	0.27
5	-0.05	-0.11	0.12
6	-0.05	-0.12	0.01
7	0.22	0.38	-0.05
8	-0.29*	-0.29*	-0.30*
9	-0.13	-0.16	-0.12
10 (large)	-0.21*	-0.24	-0.12

B) Government

Gov.	Model Bias (%)	Model Bias 2014 (%)	Model Bias 2015 (%)
Yes	-0.21*	-0.37*	-0.04
No	0.02	0.04	0.00

C) Bank country of origin

Country	Model Bias (%)	Model Bias 2014 (%)	Model Bias 2015 (%)
Hungary	4.18	4.79	3.57
Cyprus	1.29	1.71	0.88
Italy	0.79*	0.76*	0.83*
Spain	0.31*	0.40	0.23
Malta	0.24	-0.04	0.52
Austria	0.01	0.24	-0.23
Latvia	-0.09	-0.42	0.25
Norway	-0.21	-0.31	-0.12

Table 11: Heterogeneity in Model Prediction *(CONT'D)*

C) Bank country of origin

Country	Model Bias (%)	Model Bias 2014 (%)	Model Bias 2015 (%)
Luxembourg	-0.22	-0.21	-0.23
Germany	-0.26*	-0.35*	-0.17*
Netherlands	-0.28*	-0.29*	-0.27*
France	-0.30*	-0.29*	-0.27*
Belgium	-0.31*	-0.36	-0.25
Denmark	-0.34*	-0.16	-0.52
Finland	-0.34*	-0.39	-0.29
Portugal	-0.35*	-0.33	-0.37
Sweden	-0.36*	-0.43*	-0.29*
Poland	-0.40*	-0.40*	-0.39*
United Kingdom	-0.46*	-0.50	-0.41
Slovenia	-0.57*	-0.55	-0.58
Ireland	-0.66	-0.91	-0.42

* $p < 0.05$

Table 12: Banking System Fragility, Scenario Bias and Model Prediction Bias

Correlation between banking system *ex ante* fragility, scenario bias and model prediction bias. Banking system *ex ante* fragility is proxied by the country average baseline loss rate for the corporate ($loss_j^{base,corp}$) and retail portfolios ($loss_j^{base,retail}$). g^{real}, π^{real} and u^{real} are, respectively, the *realized* real GDP growth, inflation and unemployment rates in 2014 and 2015. g^{base}, π^{base} and u^{base} are, respectively, the real GDP growth, inflation and unemployment rates in the stress test *baseline* scenario. *Model Bias* is the difference between loan loss provisions over total loans and model losses predictions over credit exposure *minus* the mean error for the whole sample of banks in 2014 and 2015.

	Model Bias (%)
Model Bias (%)	1
$g^{real} - g^{base}$	0.04
$\pi^{real} - \pi^{base}$	-0.12
$u^{real} - u^{base}$	-0.19*
$loss_j^{base,corp}$	0.19*
$loss_j^{base,retail}$	0.38*

* $p < 0.05$

Table 13: Deviations from Baseline Predictions in the 2011 Stress Test

Regressions of bank loan loss provisions over total loans on stress test losses predictions with realized macroeconomic data in 2011 and 2012. *Exp. loss / Exposure* is defined as model prediction of credit losses over bank's credit exposure. *Baseline ST losses / Exposure* is the loan losses under the stress test baseline scenario in 2011 and 2012 as published by the European Banking Authority (EBA) over bank's credit exposure.

	Provisions / Loans				$\frac{Provisions}{Loans} - \frac{Baseline\ ST\ loss}{Exposure}$		
			2011	2012		2011	2012
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline ST loss / Exposure	1.841***	1.672***	1.669**	1.656***			
	(0.324)	(0.385)	(0.654)	(0.376)			
Exp. loss / Exposure		0.615	0.735	0.580			
		(0.585)	(1.671)	(0.470)			
(Exp. - Baseline ST loss) / Exposure					0.688*	0.821	0.527
					(0.387)	(0.611)	(0.396)
Constant	-0.003*	-0.005*	-0.006	-0.000	0.003*	0.002**	0.011***
	(0.002)	(0.003)	(0.008)	(0.004)	(0.001)	(0.001)	(0.002)
Year dummy	Y	Y			Y		
Adjusted R^2	0.4	0.42	0.43	0.38	0.07	0.071	0.011
Observations	124	122	60	62	122	60	62

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

Figure 1: Baseline losses vs. unemployment rate baseline scenario error