

Modeling Your Stress Away*

Friederike Niepmann and Viktors Stebunovs[†]

Abstract

We investigate systematic changes in banks' projected credit losses between the 2014 and 2016 EBA stress tests, employing methodology from Philippon et al. (2017). We find that projected credit losses were smoothed across the tests through systematic model adjustments. Those banks whose losses would have increased the most from 2014 to 2016 due to changes in their exposures and supervisory scenarios—keeping the models constant—saw the largest decrease in losses due to model changes. Model changes were realistic and more pronounced for banks that rely more on the Internal Ratings-Based approach, and they explain the cross-section of market responses to the release of the 2016 results. Stock prices and CDS spreads increased more for banks with larger reductions in projected credit losses due to model changes, as investors apparently did not interpret lower loan losses as reflecting a decrease in credit risk but, instead, as a sign of lower capital requirements going forward.

Keywords: stress tests, financial institutions, regulation, credit risk models

JEL-Codes: G21, G28

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[†]The authors are staff economists in the Division of International Finance, Board of Governors of the Federal Reserve System, Washington, D.C. 20551 U.S.A. The views in this paper are solely the responsibility of the author(s) and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System. You can contact the authors at Friederike.Niepmann@frb.gov and Viktors.Stebunovs@frb.gov.

1 Introduction

Approaches to stress testing differ across countries, notably between the European Union and the United States. In the EU-wide stress tests that are administered by the European Banking Authority (EBA), each bank builds and runs its own models following a common methodology set by the EBA. The individual banks' quantitative results are published and used by the regulators to evaluate banks' capital needs. In the United States, stress testing under the Dodd Frank Act also consists of bank-internal stress tests but these remain confidential and are, to a large extent, used to assess the quality of banks' risk management. The quantitative assessment of whether banks have enough capital that is made public is based on models that are developed and run by the Federal Reserve following an "industrywide approach, in which the estimated model parameters are the same for all BHCs."¹ Discussions between banks and regulators as to the advantages and disadvantages of the various approaches are ongoing.²

This paper highlights a possible disadvantage associated with supervisors' reliance on bank-internal models for quantitative assessments: The models can be subject to strategic adjustments, meaning banks' internal models are modified each time stress tests are run to minimize losses given the applicable scenarios and exposures. Such model changes can be unrelated to the performance of the models in predicting actual loan losses.

To estimate the credit loss models that are run by the banks, the paper follows the methodology in Philippon et al. (2017).³ Because the EBA publishes very detailed information on individual banks' hypothetical loan loss rates, it is possible to infer the relationship between macroeconomic variables and banks' credit losses using regression techniques. The data give individual banks' loss rates by portfolio, country, scenario, and forecast year. Allowing for a country-specific effect of macro variables (GDP growth, inflation rate, unemployment rate) on loan loss rates (that is the same for all banks) and, in turn, a bank-specific effect of macro variables (that is the same across countries) on loss rates, the estimation delivers approximations of banks' underlying credit loss models.

To compare the 2014 and 2016 EBA stress tests, we estimate the banks' credit models separately for the two years. This allows us to decompose changes in credit losses between stress test years. In particular, we separate the effects of changes in banks' credit exposures

¹See page 13 of "Dodd-Frank Act Stress Test 2017: Supervisory Stress Test Methodology and Results".

²Covas (2017) argues that letting banks use own models to determine equity payouts will significantly reduce the uncertainty around capital planning, and, therefore, increase efficiency and credit availability.

³Philippon et al. (2017) evaluate the informational content of and potential biases in the 2014 edition of the EBA stress, including a comparison to the 2011 edition. They do not analyze the 2016 edition in contrast to this paper.

from the effects of changes in supervisory macroeconomic scenarios and underlying bank-specific models. This exercise delivers several key results. First, changes in banks' credit exposures from 2013:Q4 to 2015:Q4, the two reference points of the stress test editions, helped lower losses. Second, the 2016 adverse scenario was less severe than the 2014 adverse scenario. Based on the same credit exposures and the same credit loss models, the 2016 adverse scenario produces lower aggregate losses than the 2014 adverse scenario. Moreover, the increase in losses between the baseline scenario and the adverse scenario is smaller in 2016 compared with the increase in 2014.⁴ The third key finding relates to model adjustments. The credit loss models appear to be tailored to each year's scenarios and exposures, that is, the 2014 (2016) models produce lower losses than the 2016 (2014) models with 2014 (2016) exposures and scenarios, and vice versa.

We explore the relationship between exposure, scenario, and model changes further, with a focus on changes at the individual bank level. Supervisory scenarios are published after bank exposures are fixed.⁵ Therefore, banks cannot adjust exposures to improve stress test results. We also find no evidence that scenarios are designed to offset changes in losses resulting from exposure changes. If anything banks that saw their losses increase due to exposure changes also saw their losses increase due to scenario changes.

We then demonstrate systematic model adjustments. To this end, we compute the losses that each bank would have incurred based on the 2016 and 2014 models using the same exposures and scenarios. We denote the difference in losses from model changes by ΔM . We also calculate the losses that result from the 2014 exposures and scenarios and, separately, from the 2016 exposures and scenarios, keeping the model constant. This difference in losses from exposure and scenario changes is denoted by ΔES . Relating changes from model changes with changes from exposure and scenario changes, we find a strong negative correlation. That is, banks whose losses would have increased the most due to exposure and scenario changes had they used the 2014 models for the 2016 stress test adjusted their models the most to lower the losses given the 2016 exposures and 2016 scenarios. Regressing ΔM on ΔES delivers a coefficient that is significant at the 1 percent level (50 observations) and an R^2 of 27 percent.

To assess the quantitative relevance of model changes, we ask how much higher losses would have been in the 2016 edition had banks used the 2014 models. In this case, losses would have increased on average by an amount equivalent to 2.8 percent of a bank's Common Equity Tier

⁴The notion of severity here is based on the outcomes for banks not on the macro-economic scenarios themselves, which is more typical in the stress test literature.

⁵Exposures are as of December 31 while stress test scenarios are published several months into the following year.

1 (CET1 capital) in the adverse scenario, with substantial heterogeneity across banks. The top 20 banks benefiting from model changes would have seen an increase equivalent to an average of 12 percent of their CET1 capital.

The systematic nature of the model changes points to strategic adjustments. In fact, changes in the riskiness of banks' portfolio, as we show, cannot explain model changes. Model adjustments might have been helped by two factors. First, banks with a larger share of exposures subject to the Internal Ratings-Based (IRB) approach saw their credit losses increase more because of exposure and scenario changes. The IRB approach is more amenable to changes since banks have more flexibility to modify models under this approach. We find that these banks indeed did so, even when controlling for exposure and scenario changes. Second, exposure and scenarios changes affected banks with more realistic models more. These banks might, therefore, have had more room to decrease projected losses than banks whose models vastly underpredicted loss rates. Ultimately, model changes between 2014 and 2016 led to convergence in model performance across banks, that is, the increase in losses from model changes was more pronounced for banks whose models under-predicted credit losses more in 2014. Therefore, the overall power of banks' credit risk models, despite the strategic adjustments, stayed roughly the same and, if anything, improved slightly in 2016.

Finally, we look at the informational content of model changes for equity and debt markets in the cross-section of stock prices and CDS spreads. Model changes ΔM have some predictive power for the cumulative changes in stock prices and CDS spreads on the first two days after the release of the stress test results. In contrast, exposure and scenarios changes have no predictive power. The larger the decrease in losses due to model changes was, the higher were abnormal stock returns. European supervisors use stress test results to set regulatory capital requirements for the following year. Thus model changes resulting in lower than expected projected losses came as a positive surprise to equity investors, who consequently anticipated higher dividends and a lower risk of dilution through new equity issuance. Had equity investors taken the lower than expected losses as a sign of reduced credit risk, one should have seen stock prices fall on the news.⁶ In line with the response of stock prices, CDS spreads increased more for banks with lower losses due to model changes, with a weaker effect for better capitalized banks. Again, a decrease in projected credit losses was seen as an increase not a decrease in risk, which is supportive of our main finding, that model changes were not related to changes in the riskiness of bank portfolios but were instead made with the intent to lower projected credit losses.

⁶An increase in risk is typically good news for equity investors due to their limited liability. So a decrease in the riskiness of a bank's loan portfolio should, if anything, have a negative effect on the bank's stock price.

2 Literature

Since stress tests are a relatively new addition to the microprudential supervisory toolkit, the literature on stress testing is small but growing. This paper builds on recent work by Philippon et al. (2017), who analyze the 2011 and 2014 EBA stress tests. The authors find that the stress tests have informational value and report no evidence for biases in the construction of the scenarios or in the estimated losses across banks of different sizes and ownership structures.⁷ Bird et al. (2015) examine potential biases in the Federal Reserve’s regulatory disclosures of the Comprehensive Capital Analysis and Review (CCAR) results. They find that the Federal Reserve appears to bias projected capital ratios upwards to prop up large banks, but downwards to discipline poorly capitalized banks. These biases appear to affect bank behavior: Banks with more positive bias in their reports are less likely to improve capital ratios by raising equity or cutting dividends subsequent to CCAR.

Another strand of the literature has studied the predictability of stress test results. Glasserman and Tangirala (2015) state that, as the CCAR process has evolved, its outcomes have become more predictable. They find that projected stress losses in the 2013 and 2014 stress tests are nearly perfectly correlated for banks that participated in both rounds. Gallardo et al. (2016) point out that, despite variations in scenarios, models, and capital distributions, CCAR stress test results have begun to stabilize which allows banks to estimate Federal Reserve-projected results more precisely and calibrate their capital actions accordingly.⁸ As a result, more sophisticated banks—such as investment, universal, and custodian banks—manage their capital in excess of regulatory minimums more aggressively. In turn, the equity market appears to reward banks’ aggressive capital requests, even if they are, at first, rejected by the Federal Reserve.

Several papers have analyzed biases in bank internal risk models. Behn et al. (2016) show that the introduction of model-based capital regulation in Germany biased downward the measurement of credit risk by banks that adopted the model-based approach. In particular, they show that internal risk estimates underpredict actual loan default rates; that both default rates and loss rates are higher for loans that were originated under the model-based approach while the corresponding risk-weights are significantly lower; and that banks that adopted the

⁷Using different methodology, Flannery et al. (2017) show that U.S. stress tests produce information: Stress test disclosures are associated with significantly higher absolute abnormal returns, as well as higher abnormal trading volume. Similarly, Petrella and Resti (2013) find that the 2011 EBA stress tests produced information, studying the response of stock prices to the publication of the results.

⁸Per Covas (2017) though, the disagreement between banks own projections and the Federal Reserves are persistent but only predictable in part.

model-based approach have lower capital charges and, at the same time, experience higher loan losses. They also find that such behavior has real effects. Large banks, the main beneficiaries of the reform, expanded their lending at the expense of smaller banks that did not introduce the model-based approach. The evidence on biases in model outputs is not limited to Europe. Using U.S. supervisory data on syndicated loans (a subset of corporate loans), Plosser and Santos (2014) show that low-capital banks bias downward their internally-generated risk estimates consistent with an effort to improve their regulatory capital ratios.⁹

Supervisory stress tests and regulatory risk weights have also been challenged by evidence from market-price-based stress tests introduced in Acharya et al. (2012). Steffen (2014) and Steffen and Acharya (2014) find that market-based metrics result in substantially higher estimates of capital shortfalls than the ECB results in 2011. In turn, Acharya et al. (2014) question the use of static regulatory risk weights in determining adequate levels of bank capitalization. They show that the risk measures used in risk-weighted assets are cross-sectionally uncorrelated with market measures of risk which may indicate that banks are gaming risk weights.

3 Background on European Stress Tests

In the EU, the European Banking Authority (EBA) coordinates and conducts microprudential stress tests in cooperation with national supervisors and regulators (ECB, Bank of England and so on). The latest two EBA stress tests ran in 2014 and 2016, aimed at evaluating the capital adequacy of major EU banks. In the stress tests, banks are given a baseline and an adverse macro-financial scenario and have to forecast capital ratios under stress over a three-year horizon following a common methodology. Banks rely on their own bottom-up models and have to assume a static balance sheet.¹⁰ The firms submit their projections to the supervisors, who scrutinize the projections and benchmark them against outcomes of a supervisory challenger model.¹¹ The final projections may reflect adjustments made by the supervisors after discussions of the original submissions with the banks. A summary of results is released by the EBA along with detailed projections for individual banks, which we make use of in this paper. The biggest source of losses for banks in the adverse scenario are credit losses and we focus on this component

⁹For related work, see Begley et al. (2017), Mariathasan and Merrouche (2014), and Vallascas and Hagendorff (2013).

¹⁰The static balance-sheet assumption means that all balance-sheet elements are kept constant throughout the test horizon. The 2014 stress-test methodology allowed exemptions from this assumption for banks under approved and likely to be completed restructuring plans that were put in place prior to December 31, 2013.

¹¹From the 2016 methodological note of the EBA stress tests: “In all circumstances, banks will be expected to identify their material risks [...] and these will be subject to challenger models from supervisors.”

of the stress tests in this paper.

While in 2014, the EBA set hurdle rates for individual banks and required banks whose capital ratios fell below those thresholds to raise fresh capital, the 2016 stress tests did not work with hurdle rates. Instead, the results were used as one element to help supervisors determine banks' capital adequacy. For euro-area banks, the stress test results feed into the SSM's Supervisory Review and Evaluation Process that sets an individual bank's Pillar II capital requirements. Therefore, the outcome of the stress tests are relevant for investors by influencing banks' capital needs and, consequently, their scope for capital distributions.¹²

While the stress tests are microprudential in nature and have the goal of assessing individual banks' capital adequacy, the results matter for macro-prudential policy as Constancio (2016) emphasizes. The aggregate results are used by the ECB to analyze potential macroeconomic effects of more stringent capital requirements as well as contagion effects across banks, for example. Moreover, the results can feed into analysis of the appropriateness of macroprudential measures. In this regard, the relevance of the stress test goes beyond the microprudential scope.

4 The Empirical Model

4.1 Model equations

This section introduces the methodology used to back out the credit loss models banks employed when projecting credit losses in the EBA stress tests. Following Philippon et al. (2017), we estimate the relationship between macroeconomic variables and banks' projected loan loss rates using a two-step procedure. In the first step, country-specific weights on macroeconomic variables are estimated via OLS:

$$\log \frac{l_{ijt}^p}{(1 - l_{ijt}^p)} = \alpha_i^p + \theta_j^p \mathbf{y}_{jt} + \epsilon_{ijt}^p, \quad (1)$$

where l_{ijt}^p is the impairment rate of bank i in scenario year t on portfolio p in country j . \mathbf{y}_{jt} is a vector of macroeconomic variables and α_i^p are bank-fixed effects.

The estimated weights $\hat{\theta}_j^p$ associated with the macroeconomic variables are used to compute country-specific macro factors: $F_{jt}^p = \hat{\theta}_j^p \mathbf{y}_{jt}$. These factors enter the regression equation that is

¹²In extreme cases, the findings may serve as inputs into the ECBs decision to declare a bank failing or likely to fail, which could lead to a resolution of a bank or to a severe dilution of its shareholders.

estimated in the second step as follows:

$$\log \frac{l_{ijt}^p}{(1 - l_{ijt}^p)} = \alpha_i^p + \beta_i^p \times F_{jt}^p + \epsilon_{ijt}^p. \quad (2)$$

β_i^p is the portfolio- and bank-specific sensitivity of loss rates with respect to the macrofactor F_{jt}^p . The model is estimated for the retail and corporate portfolios separately, hence, $p \in \{\text{retail, corporate}\}$. The macroeconomic variables that enter the regressions are GDP growth, the unemployment rate, and the inflation rate for each country j .¹³

This approach effectively links macroeconomic scenarios to credit loss projections allowing for differences across countries in how macroeconomic variables map into losses. It further allows for differences in the riskiness of bank portfolios and their sensitivities to macro developments, thereby accounting for differences in banks' business models and in the clients they cater to. To analyze changes in banks' stress test models across years, the two-step procedure is run for the 2014 and the 2016 stress tests, separately.

The stress test data are publicly available for a larger number of banks in 2014 compared with 2016. Because we do not want differences in parameter estimates across stress test editions to be driven by changes in the underlying sample of banks, we estimate the 2014 and 2016 models on the same sample of 50 banks.¹⁴

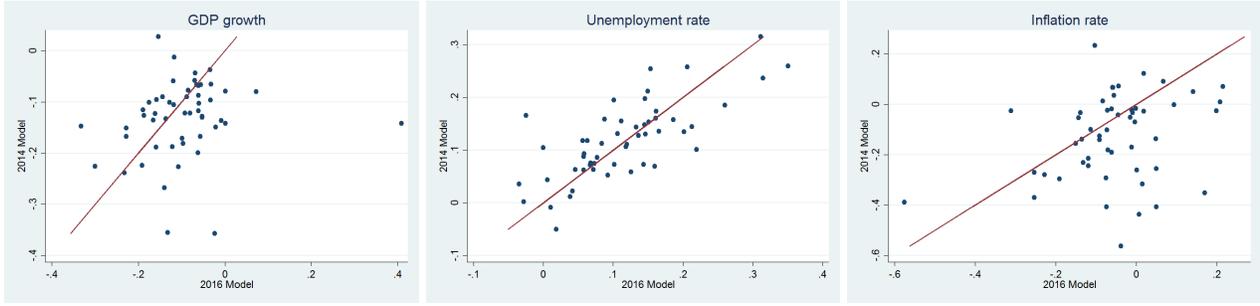
4.2 Estimation results

Weights on macro variables Results from the first-stage regressions are presented in figure 1. In each of the three panels, the country-specific coefficients $\hat{\theta}_j^p$ obtained from the 2014 data are plotted against those resulting from the 2016 data. The left (middle) panel shows the coefficients for GDP growth (the unemployment rate). The right panel is for the inflation rate. All panels also show the 45-degree line. Table 1 gives summary statistics of the coefficients. As expected GDP growth has a negative effect on loss rates while the unemployment rate has a positive effect. The effect of the inflation rate is more mixed. In the 2016 model, the unemployment rate has, on average, a larger weight than in the 2014 model, while GDP growth has a lower weight.

¹³Information on scenario GDP growth, inflation rates, and unemployment rates is provided by the EBA. We experimented with the inclusion of other, mostly financial variables. Because of little variation in these variables and collinearity with some of the included macro variables, we ended up not including them.

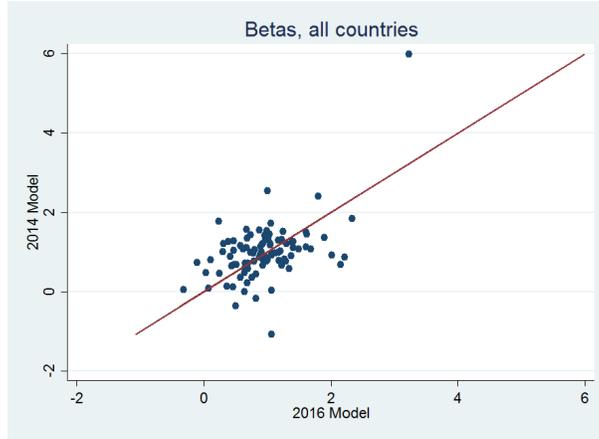
¹⁴We also estimated the 2014 model by including all banks for which information is available in the sample. All of the results presented in this paper continue to hold.

Figure 1: The estimated coefficients associated with the macro variables



Note: In each panel, the coefficients associated with one of the three macro variables that result from estimating the 2014 model are plotted against those resulting from estimating the 2016 model. The left panel shows the coefficients associated with GDP growth. The middle panel is for the unemployment rate. The right panel is for the inflation rate.

Figure 2: The estimated bank-specific β s



Note: This chart plots the β coefficients of the 2014 model against those of the 2016 model.

Banks' β s The bank-specific sensitivities to the macro factors obtained from the second-stage estimation are presented in figure 2. As can also be seen from the last two rows of table 1, there is substantial variation in bank-specific β s across banks. the average β is close to 1 by construction, but the standard deviation is relatively high at 0.53 in 2016 and 73 in 2014.

Model fit The fit of the model in terms of the R^2 , shown in table 2, is good, ranging between 53 and 65 percent depending on the stress test year and the portfolio. The R^2 displayed in the third line of the table, which is for the 2016 model estimated without the inclusion of fixed effects in the second-stage regression, indicates that macro factors alone have significant explanatory power. However, systemic differences across banks in the level of the loss rates also

Table 1: Summary of model coefficients

	mean	median	std.
GDP growth (2014)	-0.132	-0.125	0.076
GDP growth (2016)	-0.097	-0.094	0.105
inflation rate (2014)	-0.105	-0.062	0.180
inflation rate (2016)	-0.053	-0.058	0.134
unemployment rate (2014)	0.127	0.128	0.075
unemployment rate (2016)	0.115	0.109	0.085
β (2014)	0.990	0.974	0.728
β (2016)	0.958	0.932	0.533

Note: This table shows summary statistics for the coefficients that are estimated using either the 2014 or the 2016 stress test data. Std. stands for standard deviation.

play an important role in explaining the data. In 2016, a slightly larger share of the variation in retail loss rates is explained with fixed effects, and, for the corporate portfolio, the model fit is significantly better in 2014.

4.3 Model performance

Approach To assess the predictive power of the 2014 and 2016 models, we follow Philippon et al. (2017) and compare projected loan loss rates to realized loan loss rates. Information on banks' incurred loan losses is not available at the country-portfolio level. We therefore have to contrast model predictions with observed loss rates at the bank-year level, which we calculate from SNL data as annual loan loss reserves over gross loans. The sample covers the period from 2013 to 2016 and 45 banks.¹⁵ To project loss rates based on the 2014 and the 2016 models, we first obtain actual GDP growth, inflation rates and unemployment rates for the countries in our sample from 2013 to 2016.¹⁶ We then feed the models with these variables to obtain loss rates by bank, country and year. Finally, we use banks' exposures both from the stress tests and transparency exercises and sum losses to compute the average loss rate in year t for bank i as:

$$\frac{L_{it}}{\text{exposure}_{it}} = \frac{\sum_p \sum_j \frac{\exp(\alpha_i^p + \beta_i^p \times (\theta_j^p y_{jt}^p))}{1 + \exp(\alpha_i^p + \beta_i^p \times (\theta_j^p y_{jt}^p))} \times \text{exposure}_{ijt}^p}{\sum_p \sum_j \text{exposure}_{ijt}^p}, \quad (3)$$

where L_{it} represents the loan losses of bank i in year t .¹⁷

¹⁵Information on loan loss provisions was only available from SNL for 45 of the 50 banks.

¹⁶Data on realized macroeconomic variables are from the World Bank's World Development Indicators.

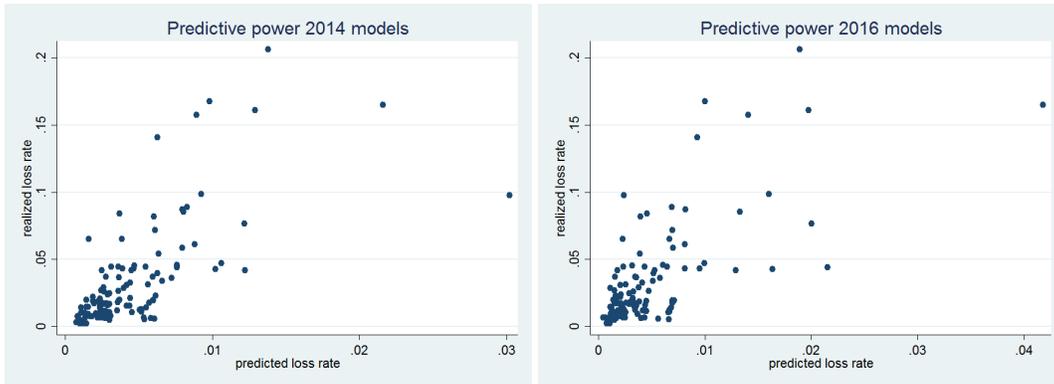
¹⁷We use 2013:Q4 exposures to project loss rates that are compared to 2013 observed loss rates. The mapping for the other years is as follows: 2014:Q4 exposures for 2014 loss rates, 2015:Q4 exposures for 2015 loss rates,

Table 2: Model estimation results: R^2

	corp	retail
	2016 Edition	
Observations	1,715	1,613
R^2	0.578	0.699
R^2 , no FE in 2nd step	0.477	0.421
	2014 Edition	
Observations	1,791	1,641
R^2	0.694	0.703
R^2 , no FE in 2nd step	0.592	0.507

Note: This table presents the number of observations and the R^2 from estimating equation 2. The equation is estimated four times: for each stress test edition and portfolio (corporate or retail) separately. The upper (lower) panel is for the 2016 (2014) edition of the stress tests.

Figure 3: Projected loss rates versus realized loss rates



Note: The two charts in the figure plot loss rates for the years 2013 to 2016 that follow from the estimated stress test models against realized loss rates, which are proxied by banks' ratios of loan loss reserve over gross loans. Data on realized reserves and gross loans is from SNL. The left (right) panel presents loan loss rates that were projected using the 2014 (2016) model.

Table 3: Indicators of model performance

	All years, all banks	
	2014 model (1)	2016 model (2)
R^2	0.484	0.504
Rank correlation	0.6893	0.6587
Sum of squared errors	0.25	0.24
Observations	129	129

Note: This tables presents different performance measures for the 2014 and the 2016 models. The R^2 and the sum of squared errors were obtained from a regression of realized loss rates on projected loss rates for the years 2013 to 2016. The first column shows the performance of the 2014 model, the second column is for the 2016 model. The rank correlation coefficient shown is Spearman’s rank correlation coefficient.

Overall performance Figure 3 plots actual bank loan loss rates against the predicted loss rates, showing that the models have significant predictive power for observed loss rates. Of note, observed loss rates are significantly higher than projected loss rates. This is not only true for the loss rates that follow from the 2014 and the 2016 models, but also for the loss rates that the banks reported for the baseline scenario. The likely reason for this is that SNL uses a different definition of provisions and gross loans than the banks themselves. We therefore attribute the discrepancy to external factors and do not think there is a flaw in the banks’ or our projections in that respect.

The difference in the levels notwithstanding, we assess the performance of the models based on several performance measures: The R^2 and the sum of squared errors of a regression of realized loss rates on projected loss rates, as well as Spearman’s rank correlation coefficient. Overall differences in the performance of the models appear small as table 3 indicates, with the 2016 model performing slightly better. We investigate model performance further in section 6.

2016:Q2 exposures for 2016 loss rates. Data for 2014:Q4 and 2016:Q2 is from the transparency exercises that took place in these years.

5 Decomposing Changes in Credit Losses

5.1 Aggregate analysis

With the estimated 2014 and 2016 models and data at hand, we can investigate various factors that contributed to changes in banks' credit losses between stress tests. To this end, we conduct counterfactual analysis, asking what banks' credit losses would have been, had exposures, models or scenarios remained the same. Table 4 shows the results. To illustrate the logic of the table, consider the top part of the table under columns (1), titled m16/s16/e16. m stands for model, s for scenario, e for exposure, and the number reflects the year of the stress test. The aggregate losses of EUR 179 billion result from the 2016 model applying the banks' 2016 exposures (as of 2015:Q4) and using the macro variables from the 2016 adverse scenario. Equivalently, the numbers under m16/s14/e14 provide the aggregate credit losses of banks resulting from the 2016 model but using the banks' 2014 exposures (as of 2013:Q4) and the 2014 scenarios. In the calculation of each number, we input values for the macro variables, predict loss rates by bank, country and scenario using the respective model, multiply loss rates with exposures and sum losses across banks, portfolios, countries and years.¹⁸

Analyzing the losses shown in table 4, four facts emerge. First, the 2016 adverse scenario was less severe than the 2014 adverse scenario in terms of credit losses. Comparing column (1) and column (3), we observe that losses are larger for the 2014 scenario using the 2014 model as well as the 2016 model. The EBA adverse scenario is designed as a shock to the baseline. One might therefore want to judge the severity of the adverse scenario by the difference between losses in the adverse scenario and the baseline scenario. By this metric, the 2016 adverse scenario also appears less severe. The increase in losses in the adverse scenario from the baseline was 103 percent in 2014 but only 75 percent in 2016.

Second, reductions in credit exposures from 2013:Q4 to 2015:Q4 contributed to lower credit losses. Keeping the model and scenarios fixed, 2014 exposures produce higher losses compared with 2016 exposures, no matter which model and scenario is used for this comparison.

Third, the credit loss models were subject to adjustments that lowered the losses that the stress tests produced. This can most clearly be seen by comparing the numbers in column (1) with those in column (4). Start by comparing the losses of the 2016 and 2014 models with the 2016 exposures and scenarios. The 2014 model produces higher losses than the 2016 model when the 2016 exposures and scenarios are applied. Next, consider the losses of the 2014 and

¹⁸We make sure that losses are always summed over the same number of bank-country observations.

Table 4: Counterfactual credit losses, in EUR million

	model/scenario/exposure			
	(1)	(2)	(3)	(4)
	m16/s16/e16	m16/s16/e14	m16/s14/e16	m16/s14/e14
adverse	178,866	188,998	348,230	387,484
baseline	102,165	108,025	156,614	172,433
	m14/s14/e14	m14/s14/e16	m14/s16/e14	m14/s16/e16
adverse	253,764	236,812	246,372	237,138
baseline	124,580	115,593	105,297	100,679
	mb16/sf14/e14		mb14/sf16/e16	
adverse	212,451		240,237	

Note: This table shows banks' aggregate credit losses that follow from different counter-factual exercises. The title above each figure in the table indicates the exercise. For example, m16/s16/e16 reflects the aggregate losses of banks that result from the 2016 model, the 2016 scenario and 2016 exposures. As another example, m14/s16/e14 indicates the banks' aggregate losses that result from the 2014 model, the 2016 scenario and 2014 exposures. mb16/sf14/e14 stands for the losses that result when applying the 2016 bank-specific β s and fixed effects, the 2014 macro factors F_j^p as well as 2014 exposures. To obtain each number, the scenario macro variables are plugged in and used to predict loss rates by bank, country and scenario based on the respective model. Loss rates are multiplied with exposures and losses summed across banks, portfolios, countries and years.

2016 models with the 2014 exposures and scenarios. In this case, the 2016 model produces higher losses. Thus each model produces the lowest losses for the scenarios and the exposures that applied in year the model was used.¹⁹

Forth, model changes were such that macroeconomic variables had a stronger overall effect on loss rates in 2016 compared to 2014. However, bank-specific sensitivities and fixed effects lowered overall losses more in 2016 than in 2014. To see this, compare the bottom row in column (1) with the middle row of column (1) and the top row of column (4). mb16/sf14/e14 stands for the losses that result when 2014 exposures, 2014 factors (F_j^p), and 2016 fixed effects and bank sensitivities (β_j^p) are used to compute aggregate losses. The 2016 fixed effects and β s lower losses to EUR 212 billion from EUR 254 billion. Equivalently, if the 2016 weights on macro variables are used for the 2014 scenario, losses increase to EUR 387 billion.

¹⁹Banks project loss rates three years out in the stress tests.

5.2 Bank-level analysis

In the following, we investigate the various changes in credit losses further, focusing on losses in the adverse scenario. Instead of aggregating losses, we compute counterfactual losses for each bank. ΔM_i^e stands for the log change in losses of bank i stemming from model changes, keeping the scenario and exposures constant. ΔE_i^e denotes the log change in losses from exposure changes, keeping the scenario and the model constant. ΔS_i^e represents the change in losses from changes in the adverse scenarios keeping the exposures and model constant. Superscript e denotes whether the elements that are kept constant are from the 2014 test or the 2016 test.²⁰

Scenario changes We start by taking a closer look at the effects of scenario changes to investigate potential bias in scenario design, analyzing whether changes in the adverse scenario affected the credit losses of certain banks more than others. In table 5, scenario changes ΔS_i^{14} are correlated with exposure changes ΔE_i^{14} and banks' capital buffers. A bank's capital buffer is computed as its CET1 capital ratios as of 2015:Q4 minus its all-in regulatory capital requirement in 2016.²¹

Columns (1) and (2) of the table show that there is a positive correlation between scenario changes and exposure changes, implying that banks whose losses increased because of changes in exposures also tended to see an increase in losses from scenario changes. Because scenarios are published after exposures are fixed, it is not possible for banks to adjust exposures to achieve lower projected losses (better results).²² However, supervisors could probably cherry-pick scenarios based on bank balance sheets. The positive association between scenario changes and exposure changes suggests that scenarios are not chosen to offset changes in losses from changes in exposures. In columns (3) and (4), scenario changes are regressed on banks' capital buffers. While the coefficient is significant at a 10 percent level in column (3), closer inspection shows that this result is driven by one outlier. There is no robust relationship between scenario changes and capital buffers. Column (5) and (6) use as the dependent variable the change in losses from both scenario and exposure changes together. Again, there is no correlation with capital buffers. From this, we conclude that scenarios are unbiased, in the sense that changes in the scenarios affect weaker and stronger banks alike.

²⁰For example, ΔM_i^{14} is computed as $\log(m16/s14/e14) - \log(m14/s14/e14)$. Results are very similar for percent changes.

²¹The all-in regulatory capital requirement includes Pillar 1, Pillar 2, and additional buffer requirements, for example, the GSIB buffer.

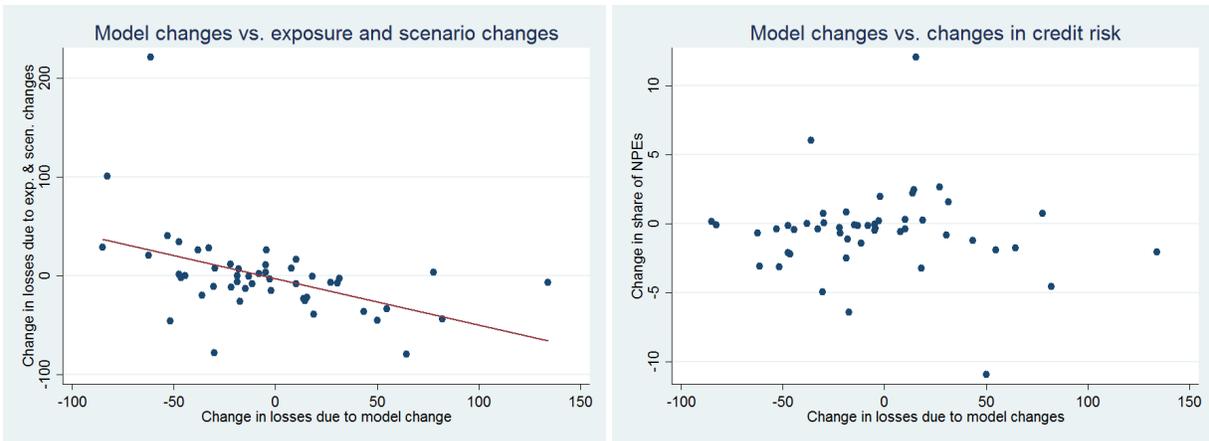
²²In 2016, scenarios were published in February 2016 and banks had to use exposures as of 2015:Q4 as a jump-off point for the projections.

Table 5: Explaining scenario and exposure changes

VARIABLES	(1) ΔS_i^{14}	(2) ΔS_i^{16}	(3) ΔS_i^{14}	(4) ΔS_i^{16}	(5) ΔES_i^{14}	(6) ΔES_i^{16}
ΔE_i^{14}	0.202 (0.142)					
ΔE_i^{16}		0.337** (0.135)				
Capital buffer			0.00342* (0.00184)	-0.00266 (0.00493)	0.00217 (0.00279)	-0.00531 (0.00609)
Constant	-0.00956 (0.0282)	-0.288*** (0.0822)	-0.109 (0.0700)	-0.256* (0.142)	-0.144 (0.0978)	-0.287 (0.175)
Observations	50	50	39	39	39	39
R-squared	0.088	0.041	0.151	0.008	0.018	0.021

Note: This tables analyzes, at the bank-level, the relationship between capital buffers and the change in losses that results from exposure changes (ΔE_i^e), from scenario changes (ΔS_i^e), or from a combination of the two factors (ΔES_i^e). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 4: Model changes, exposure and scenario changes, and changes in non-performing exposures



Note: The left panel in the figure plots model changes ΔM_i^{16} against the change in losses from scenario and exposure changes ΔES_i^{14} . The red line shows the linear relationship that results from a simple linear regression. The right panel plots model changes ΔM_i^{16} against the change in the share of banks' non-performing exposures from 2013:Q4 to 2015:Q4. For ease of interpretation Changes are in percent, except for the y-axis in the right panel, which shows the change in percentage points.

Table 6: Explaining model changes

VARIABLES	(1) ΔM_i^{14}	(2) ΔM_i^{16}	(3) ΔM_i^{14}	(4) ΔM_i^{14}	(5) ΔM_i^{14}
ΔES_i^{14}	-0.839*** (0.229)	-0.712** (0.274)			-0.756*** (0.201)
ΔNPE_i			-0.0186 (0.0351)		
$\Delta adj. NPE_i$				-0.167 (4.430)	-2.389 (3.416)
Constant	0.135 (0.0833)	-0.195** (0.0741)	0.163* (0.0944)	0.175* (0.100)	0.119 (0.0858)
Observations	50	50	48	48	48
R-squared	0.266	0.241	0.003	0.000	0.254

Note: This table investigate to what extent model changes M_i^e can be explained by scenario and exposure changes ΔES_i^{14} and changes in the riskiness of banks' loan portfolios. The latter are proxied by the change in the share of non-performing exposures of bank i from 2013:Q4 to 2015:Q4 and denoted by ΔNPE_i . $\Delta adj. NPE_i$ reflects changes in the share of non-performing exposures that cannot be explained by changes in GDP growth, the inflation rate and the unemployment rate. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Model changes Next, we study model changes by bank. Specifically, we investigate whether there is a relationship of combined scenario and exposure changes ΔES_i^e with model changes ΔM_i^e , again with a focus on the adverse scenario. The left panel in figure 4 plots the change in losses due to scenario and exposure changes ΔES_i^{14} against the change in losses due to model changes ΔM_i^{16} , displaying a clear negative relationship.²³ This suggests that banks with a larger increase in losses due to scenarios and exposure changes saw adjustments to their models that resulted in larger reductions in losses. Thus, model adjustments effectively smoothed losses for banks across the stress tests. Table 6 confirms this result based on regression analysis. In column (1) and (2), model changes are regressed on scenario combined with exposure changes. Column (1) uses 2014 exposures and scenarios to compute model changes. Column (2) is based on the 2016 exposures and scenarios. In both columns, the coefficient associated with changes in losses from scenario and exposure changes is statistically significant, in column (1) at a 1-percent level. The R^2 is high, ranging between 24 and 27 percent.

Model changes cannot be explained by changes in the riskiness of portfolios. If this factor was driving model changes, we should observe a correlation between model changes and the

²³The chart shows percent changes for ease of interpretation.

change in the share of non-performing exposures in banks' corporate and retail portfolios, a proxy for changes in the riskiness of the underlying portfolios. In column (3) of table 6, ΔM_i^{14} is regressed on the change in the share of non-performing exposures from 2013:Q4 to 2015:Q4. The right panel of figure 4 plots these two variables against each other. In column (4), the regression exercise of column (3) is repeated with changes in the share of non-performing exposures that cannot be explained by changes in macroeconomic conditions.²⁴ Excluding two outliers, there is no correlation between the model changes and changes in the riskiness of portfolios. At the same time, controlling for the change in the share of non-performing exposures does not affect the correlation between ΔM_i^{14} and ΔES_i^{14} . In light of these results, the correlation between model changes and scenario plus exposure changes strongly suggests that models are adjusted with the intent to smooth losses across the stress tests. Because banks cannot adjust their exposures in response to the scenarios given when scenarios become public, it is difficult to come up with other stories to explain the strong negative relationship between the two variables.

To understand how quantitatively relevant model changes between the stress tests are, we calculate the difference (m14/s16/e16-m16/s16/e16) for each bank as a ratio of its end-2015 CET1 capital. On average, the increase in losses that banks would have seen had they not adjusted their models was 2.8 percent of their CET1 capital in the adverse scenario. For the top 20 banks benefiting from model changes, losses would have increased on average by an amount equivalent to a substantial 12 percent of the banks' CET1 capital.

6 Model Changes: Digging Deeper

This section examines further model changes, documenting two factors that might have facilitated banks' model changes. First, banks that had a larger incentive to lower losses through model changes were those with more model flexibility because a larger portion of their exposures is subject to the IRB approach. Second, these banks' models performed better (more realistically)—that is, they underestimated loan loss rates by less—likely giving these banks more room to game projected loss rates while avoiding a lot of supervisory scrutiny.

²⁴The change in the share of non-performing exposures was calculated by combining non-performing exposures in the retail and the corporate portfolio. $\Delta adj. NPE_i$ was computed from the errors of a regression of the share of non-performing exposures of bank i in country j and year t on GDP growth, the inflation rate and the unemployment rate in country j and year t .

6.1 The role of the IRB approach and model performance

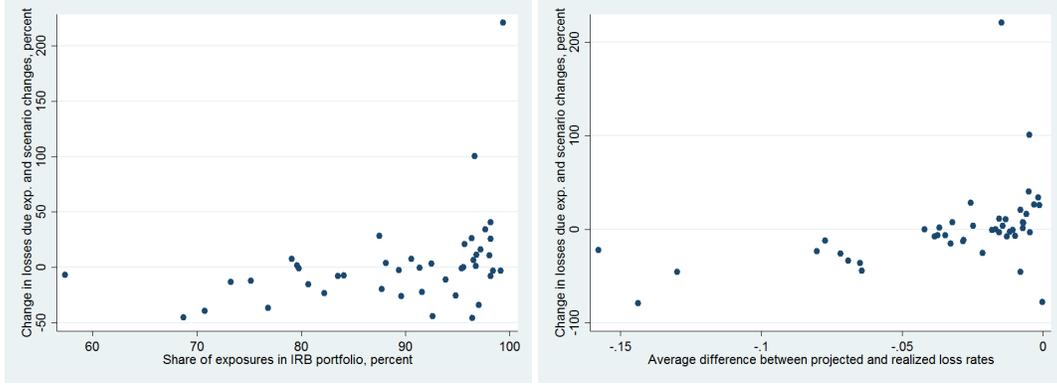
Previously, we showed that scenario and exposure changes were unrelated to each other and independent of capital buffers. However, the increase in losses from scenario and exposure changes was larger for banks with a larger share of exposures subject to the IRB approach. Banks that use the IRB approach run their own quantitative models to estimate the probability of default, exposure at default, and loss given default (and these feed into risk weights calculations). Banks using the Standardized Approach (STA), in contrast, employ ratings from external credit rating agencies to quantify these objects, which leaves less room for maneuver. In column (1) of table 7, ΔES_i^{14} is regressed on the share of a bank's IRB exposures in total exposures.²⁵ The resulting regression coefficient is significant at the 5 percent level, indicating a positive relationship between exposure plus scenario changes and the importance of the IRB approach at the bank level. This positive relationship, which can also be observed in the left panel of figure 5, might have helped model adjustments because those banks that had more flexibility in models had the biggest incentive to adjust the models.

Next, we analyze whether exposure and scenarios changes are correlated with model performance by bank. Model performance is judged using the methodology described in section 4.3. In column (2) of table 7, ΔES_j^{14} is regressed on the average difference between projected loan loss rates and observed loan loss rates resulting from the 2014 model and denoted by MP_i^{14} (also plotted in the left panel of figure 6). Note that this differences is negative in the data. The corresponding coefficient is positive and significant, suggesting that banks whose models under-predicted loan loss rates more saw a smaller increase in losses from exposure and scenario changes. The right panel of figure 5 confirms this relationship. Thus banks with the largest incentives to change models and decrease credit losses were those whose models performed better and under-predicted loss rates by less. As a result, these banks probably had more room to produce models that generate lower losses.

To study the role that the IRB approach and model performance have in explaining model changes, we next regress model changes on these factors. Columns (4) to (7) of table 7 presents the results. Column (4) shows that indeed, banks with a higher share of exposures subject to the IRB approach had model changes that resulted in a larger reduction in losses. Column (5) indicates that also banks whose models underpredicted realized loss rates by less saw a larger decline in losses from model changes. Column (7) includes both factors in the regression together with scenario plus exposure changes ΔES_i^{14} . While the coefficients associated with banks' share of IRB exposures and model performance are not significant at the 10 percent

²⁵The sample excludes banks with zero IRB exposures.

Figure 5: The role of the IRB approach and model performance



Note: The left panel of this figure plots the bank-specific change in credit losses from exposure and scenario changes between stress test editions (ΔES_i^{14}) against the the share of a bank's exposures subject to the internal risk based approach as of 2015:Q4. In the right panel ΔES_i^{14} is plotted against the average difference between loss rates projected using the 2014 model and observed loss rates for the period from 2013 to 2016. Scenario and exposure changes in this chart were computed as percent changes rather than log changes.

Table 7: The role of the IRB approach and model performance, regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ΔES_j^{14}	ΔES_j^{14}	ΔES_j^{14}	ΔM_j^{14}	ΔM_j^{14}	ΔM_j^{14}	ΔM_j^{14}
IRB share	0.0129** (0.00507)		0.00524 (0.00429)	-0.0284** (0.0111)			-0.0148 (0.0103)
MP_i^{14}		5.932** (2.242)	4.377*** (1.306)		-8.543** (3.439)		-4.799 (3.790)
ΔES_j^{14}						-1.160*** (0.342)	-0.729** (0.312)
Constant	-1.183** (0.439)	0.107 (0.0944)	-0.353 (0.377)	2.703*** (1.000)	-0.0648 (0.126)	0.158* (0.0907)	1.351 (0.949)
Observations	44	45	42	44	45	42	42
R-squared	0.156	0.249	0.305	0.166	0.215	0.282	0.380

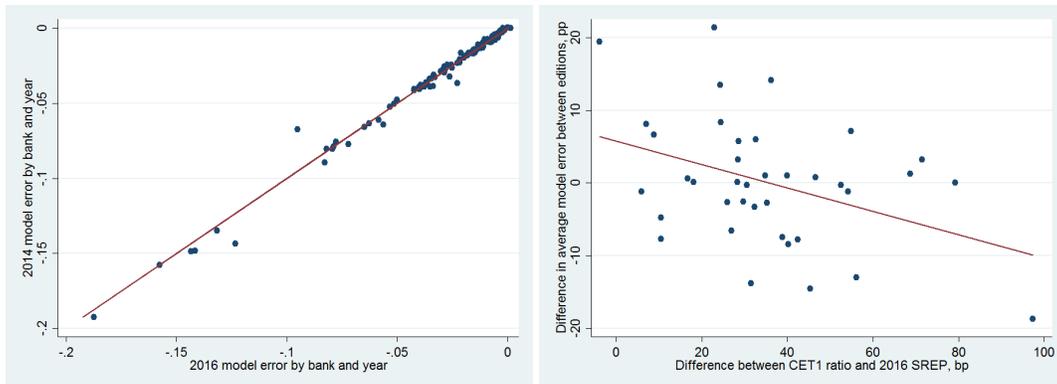
Note: This table explores the correlation between exposure and scenario changes (ΔES_i^{14}) with the share of a bank's exposures subject to the internal risk based approach as well as with its model performance (columns 1-3). It also investigate whether these two latter factors can explain the change in losses coming from model changes (columns 4-7). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

level, the coefficients maintain their signs (compare to columns 4 and 5). More importantly, the R^2 increases to 38 percent, up from 28 percent, when these variables are included (see column 7), indicating that they are relevant in explaining model changes even after controlling for banks' incentive to adjust models. At the same time, the regression shows that model changes remain strongly related to scenario plus exposure changes even when controlling for the scope of improvements in model performance.

6.2 A closer look at changes in model performance

In a final step in this section, we study how model changes affected model performance by bank. As discussed in section 4.3, the overall performance of the models in explaining realized loss rates remained very similar across stress test editions.

Figure 6: Changes in model performance by bank



Note: The left panel of the figure plots the difference between projected loss rates coming from the 2014 model and realized loss rates against the same difference coming from the 2016 model. The right panel has a bank's capital buffer on the x-axis and the change in a bank's average model error (in percent) between the 2014 and the 2016 stress test edition on the y-axis. A negative (positive) change indicates an improvement (deterioration) in model performance.

The left panel of figure 6 plots the average difference between projected loan loss rates and observed loan loss rates resulting from the 2014 model against the same difference following from the 2016 model by bank. Two facts emerge. First, there are substantial differences in model performance across banks.²⁶ Second, the performance of the models was relatively stable across stress test editions. Banks with a large gap to the observed loan loss rates resulting from the 2014 model also had a large gap based on the 2016 model. However, model performance

²⁶This fact can also be seen from figure 5.

was not constant for all banks (not all points are close to the 45 degree line) and, as it turns out, improvements in model performance were not entirely random.

The the right panel of figure 6 plots the change in a bank’s average model error (in percent) between the 2014 and 2016 stress tests against the bank’s capital buffer. As before, the capital buffer is defined as the difference between a bank’s CET1 capital ratio and its 2016 all-in capital requirement. Here, a positive (negative) change indicates a deterioration (improvement) in model performance. The positive relationship that emerges from the chart, which is also confirmed based on regression analysis, shows that banks with smaller capital buffers had bigger improvements in model performance.²⁷ This might indicate that banks with weaker capital buffers saw a stronger need to improve model performance.

To sum up, systematic model changes that effectively lowered credit losses were helped by several factors. First, banks who saw the strongest increase in losses had the biggest flexibility in modeling credit risk. Second, they had better models, meaning that their models were probably not under particular supervisory scrutiny. Finally, banks with weak capital buffers seem to have been under the biggest pressure to improve models. But the increase in losses from exposure and scenario changes was not correlated with capital buffers. This combination of factors can also explain why the overall performance of the credit loss models improved slightly despite systematic model adjustments. That said, we cannot discern exactly which model changes were solely done by the banks and which reflect negotiations between the banks and the supervisors.²⁸

7 The Market Response to the 2016 Stress Test Results

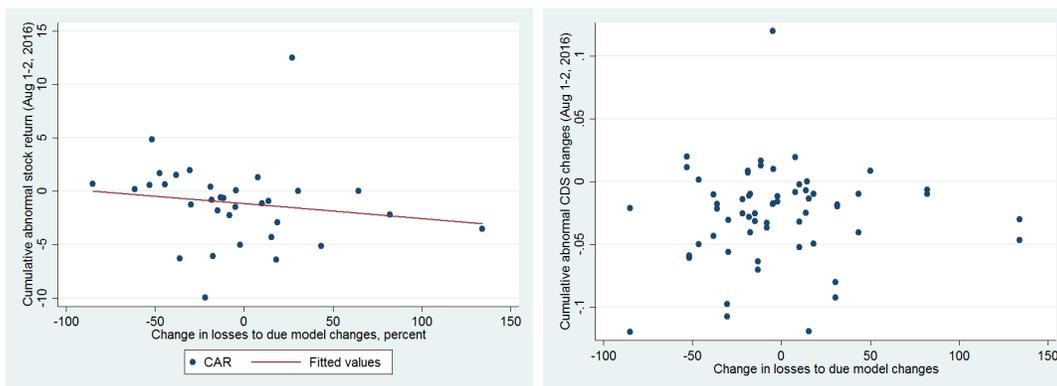
We have argued that model changes were mainly motivated by increases in losses from scenario and exposure changes between the stress tests and do not reflect changes in the intrinsic riskiness of bank portfolios. We find additional support for this hypothesis from the response of bank stock prices and CDS spreads to the publication of the 2016 stress test results.

We start by computing abnormal price changes on the first two days after the announcement

²⁷The change in the average model error was computed as the average difference in percent between projected loss rates resulting from the 2014 model and realized loss rates for the period from 2013 to 2016 minus the average difference in percent between projected loss rates using the 2016 model and realized loss rates over the same time period. The regression of the change in the average model error between the 2014 model and the 2016 model delivers a coefficient that is significant at the 3 percent level.

²⁸The projections that are made public are approved by the supervisors that oversee the stress tests. These projections may reflect adjustments by the supervisors and, therefore, may differ from the banks original projections that follow directly from the banks own models.

Figure 7: Model changes and abnormal changes in stock prices and CDS spreads, plots



Note: The left panel of the figures shows banks' cumulative abnormal stock returns on August 1 and 2, 2017 plotted against ΔM_i^{16} . The right panel plots cumulative abnormal changes in banks' CDS spreads over the same days against ΔM_i^{16} .

of the 2016 stress test results, August 1-2, 2017. Abnormal price changes are defined as changes that cannot be explained by the typical movement of a bank's stock price and CDS spread with a corresponding EU-wide index.²⁹ These abnormal changes are summed up for the two days after the publication of results. Cumulative abnormal price changes are then related to model changes ΔM_i^{16} .³⁰ Bank stock prices are available for 33 of the 51 banks (as not all banks are public). CDS spreads are for a 5-year horizon, cover both senior and subordinated bank debt and are available for 30 banks.

The left panel of figure 7 plots abnormal changes in stock prices against model changes. The chart suggests that bank equity investors earned higher abnormal returns the smaller the increase in losses from model changes was. In other words, banks that reduced credit losses through model changes more experienced higher abnormal returns. A correlation between abnormal changes in CDS spreads and model changes is not apparent from the right panel of figure 7, which has model changes on the x-axis and abnormal changes in the spreads on the y-axis. However, multivariate regression analysis reveals a systematic relationship.

Before turning to CDS spreads, consider columns (1) through (4) of table 8. While the econometric evidence is, admittedly, not particularly strong, the table, suggests the biggest predictive power for model changes consistent with the left panel of figure 7. The associated

²⁹Each bank's log change in the stock price and CDS spread is regressed on an EU-wide index for a 120-day window before the publication of the results. The residuals of these regressions are the abnormal price changes. Bank stocks are regressed on the Eurostoxx50 index, CDS spreads on the Itraxx Europe index.

³⁰We use 2016 exposures and scenarios to compute the change in losses from model changes for this exercise (ΔM_i^{16}) because this change corresponds to the effective change in losses, relevant for the 2016 stress test results.

coefficient in column (3) is significant at a 15-percent level, and the R^2 of the regression is by far the highest among column (1) to (4). The coefficient implies that a 10 percent declines in credit losses, implies a 0.14 percentage point higher return. Exposure and scenario changes, which could have been anticipated by investors, are not significant for abnormal stock returns (see columns 1 and 3).

Columns (5) through (9) repeat the exercise for abnormal changes in CDS spreads. The regression shown in column (8) includes additionally an interaction term between model changes and bank capital buffers. Once the response of CDS spreads to model changes is allowed to differ by bank capitalization, coefficients turn significant at a 10-percent level. Based on the coefficients in column (8), a bank with a 30 percent capital buffer would see an increase in its CDS spread by 6 basis points in response to a 10 percentage fall in credit losses. The negative coefficient associated with model changes together with the positive coefficient on the interaction term suggests that banks with lower losses, because of model changes, experienced an increase in CDS spreads, while effects were weaker for banks with stronger capital buffers.

What do these results imply? As discussed in Section 3, the supervisors made it clear that 2016 stress test results would be used to determine banks' capital requirements for 2017. Lower capital requirements are good news for stock holders because they imply that banks have more room to pay dividends and may not have to raise fresh capital, so that dilution risk for existing stock holders goes down. In contrast, lower capital requirements are bad news for bond holders, because there is less capital to absorb losses in the event of solvency problems at banks. With an increase in the probability that bond holders are not paid, CDS spreads should rise. The regression results are in line with this interpretation: Stock price increased more with a stronger reduction in losses from model changes, while CDS spreads also increased. If the decrease in model changes had been perceived as reflective of actual changes in risk, then we should have seen the opposite response of stock prices since a decrease in risk is typically bad for stock holders but good for bond holders. Thus, the responses of stock prices and CDS spreads to model changes are entirely consistent with strategic model adjustments that were not driven by changes in the riskiness of banks' loan portfolios and came as a surprise to investors.

Table 8: Model changes and abnormal changes in stock prices and CDS spreads, regressions

	stock prices				CDS spreads				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔES_i^{14}	1.128 (1.117)				0.0145 (0.0199)				
ΔS_i^{16}		-0.109 (0.680)				0.00638 (0.0102)			
ΔM_i^{16}			-1.408 (0.950)				0.0123 (0.0116)	-0.0418* (0.0240)	
$\Delta Total_i$				-0.756 (1.357)					0.0180 (0.0114)
Capital buffer								0.000615 (0.000413)	
$\Delta M_i^{16} \times \text{cap buf}$								0.00144* (0.000745)	
Constant	-1.011 (0.655)	-1.141* (0.671)	-1.317* (0.744)	-1.277 (0.803)	-0.0249*** (0.00558)	-0.0236*** (0.00585)	-0.0245*** (0.00485)	-0.0394*** (0.0124)	-0.0223*** (0.00541)
Observations	33	33	33	33	61	61	61	57	61
R-squared	0.015	0.000	0.034	0.008	0.008	0.011	0.025	0.091	0.046

Note: This table analyzes whether the response of stock prices and CDS spreads on the two days after the publication of the stress test results can be explained by changes in losses coming from model changes. The dependent variable in columns (1) to (4) is the cumulative abnormal stock return on August 1 and 2, 2017. The dependent variable in columns (5) to (9) is the corresponding cumulative abnormal change in CDS spreads. $\Delta M_i^{16} \times \text{cap buf}$ represents an interaction term between model changes and a bank's capital buffer defined as the difference between its fully-loaded CET1 ratio and its all-in capital requirements. $\Delta Total_i$ is the total change in credit losses between stress test editions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

8 Conclusions

Microprudential stress tests are designed to evaluate the capital adequacy of banks. Approaches across countries differ significantly, both in terms of who runs the stress tests and how the results are used. In the European Union, banks are allowed to build and run their own models to produce capital figures under stress. In line with papers in the literature on gaming risk weights, this paper shows that the flexibility that exists in the design and use of banks' own models is systematically exploited to minimize projected losses in stress tests.³¹ While banks' own models may be, in principle, best suited to assess the intrinsic credit risk on bank balance sheets, our results imply that the manipulation of projections cannot be excluded where the test results determine the prospects for capital distribution to investors. Stress test setups that leave little room for tailoring models to individual banks—for example, the top-down approach that the Federal Reserve chose for the CCAR—are less prone to this issue. If the supervisors stick to the bottom-up approach and rely on banks' own models, there should be an additional layer of checks for systemic model adjustments. Otherwise, bank stress may be modeled away.

³¹See, for example, Plosser and Santos (2014), Behn et al. (2016), and Acharya et al. (2014).

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