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“Modeling Your Stress Away”

Friederike Niepmann^{a,b,c} and Viktors Stebunovs^a

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 the supervisory scenarios—keeping the models constant and controlling for changes in the riskiness of underlying portfolios—saw the largest decrease in losses due to model changes. Model changes were 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 mainly 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 classifications: G21, G28

^a Federal Reserve Board; ^b CESifo; ^c C.E.P.R.. The authors would especially like to thank Sam Mackey for excellent research assistance. For their helpful comments, they would also like to thank Mark Carey, Ricardo Correa, Sally Davies, Rainer Haselmann, and Tim Schmidt-Eisenlohr as well as participants in seminars at the Deutsche Bundesbank, the ECB, and the Federal Reserve Board. 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.

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 Bank Holding Companies.”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 reduce 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 estimate 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 tests, 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.

We explore the relationship between exposure, scenario, and model changes further, with a focus on changes at the individual bank level. We 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. However, changes in the adverse scenario are correlated with changes in the riskiness of bank portfolios. Banks whose portfolio risk—proxied by risk-weight density—increased more between stress test years saw a relatively milder adverse scenario in 2016 compared with 2014. We conjecture that this is because changes in the adverse scenario are related to changes in countries’ macroeconomic conditions. As the economy improves, a constant shock to the baseline scenario implies a milder adverse scenario in absolute terms. At the same time, banks might increase the risk in their portfolios as the economy improves.

We then demonstrate systematic model adjustments. To this end, we compute the losses that each bank would have incurred had it applied the 2014 model in 2016 and vice versa, for the same exposures and scenario. We denote the difference in these losses, which stems from model changes, by ΔM . We also calculate the losses that result from the 2014 adverse scenario and, separately, from the 2016 adverse scenario, keeping the model and exposures constant. The difference between these losses, which stems from scenario changes, is denoted by ΔS . Relating the estimated changes from model changes with the estimated changes from scenario changes, we find a strong negative correlation. That is, banks whose losses would have increased the most due to scenario changes had they used the 2014 models for the 2016 stress test appear to have adjusted their models the most to lower the losses given the 2016 adverse scenario. Regressing ΔM on ΔS delivers a coefficient that is significant at the 1 percent level (50 observations).

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

To assess the quantitative relevance of model changes, we ask how much higher losses would have been in the 2016 stress test had banks used the 2014 models. In this case, losses would have increased on average by an amount equivalent to 1.7 percent of a bank’s Common Equity Tier 1 (CET1 capital) in the adverse scenario, with substantial heterogeneity across banks. The 10 banks benefiting the most from model changes would have seen an increase equivalent to an average of 15 percent of their CET1 capital.

The systematic nature of the model changes suggests strategic adjustments. In fact, we control for changes in the riskiness of bank portfolios by including changes in banks’ risk-weight densities between stress tests in the regressions. Yet, changes in losses from scenario changes, ΔS , continue to predict changes in losses from model changes, ΔM . We also show that reductions in losses through model changes were more pronounced for larger portfolios, where adjustments have a larger effect on a bank’s aggregate credit losses.

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 models are more complex, which likely gives banks more flexibility to adjust models under this approach. 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. Separately, we find that for banks with smaller capital buffers model performance improved more between 2014 and 2016 than for better capitalized banks, indicating that supervisors might have scrutinized the models of weaker banks more.

Finally, we look at the informational content of model changes for equity and debt markets in the cross-section of stock prices and Credit Default Swap (CDS) spreads. Model changes ΔM have 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. The larger the decrease in losses due to model changes was (controlling for changes in risk-weight densities), 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.⁵ 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 a significant portion of model changes were not related to changes in the riskiness of bank portfolios but instead served to contain and smooth projected credit losses across stress tests.

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.⁶ 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.⁷ As a result,

⁵An 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.

⁶Using 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.

⁷Per Covas (2017) though, the disagreement between banks own projections and the Federal Reserves are persistent but only predictable in part.

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 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. Begley et al. (2017) analyze bank risk in the trading book of U.S., Canadian and European banks, documenting that a decrease in a bank’s equity capital results in less informative self-reported risk measures in the following quarter. Mariathasan and Merrouche (2014) also provide evidence for manipulation of risk weights, uncovering that risk-weight density declines after regulators approve a bank’s internal model, with stronger effects for banks with weaker capitalization.⁸

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.⁹

⁸For related work, see also Vallascas and Hagendorff (2013).

⁹For papers on the effects of stress tests, for example, for bank lending, see Pierret and Steri (2017), Acharya et al. (2018), Calem et al. (2016), Bassett and Berrospide (2017) and Cortes et al. (2018).

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 of the stress tests in this paper.

While the EBA set hurdle rates for individual banks in 2014 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 Single Supervisory Mechanism's (SSM) Supervisory Review and Evaluation Process (SREP) 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.

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."

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. Also, the capital shortfall under stress puts a cap on public funds that can be injected into a bank under a precautionary recapitalization.

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:

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

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

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

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

β_i^{py} is the portfolio- and bank-specific sensitivity of loss rates with respect to the macrofactor F_{jt}^{py} in stress test y . The model is estimated for the retail and corporate portfolios separately, hence, $p \in \{\text{retail}, \text{corporate}\}$. To analyze changes in banks' stress test models across years, the two-step procedures is run for the 2014 and the 2016 stress tests separately, hence, $y \in \{2014, 2016\}$. 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.

In what follows, we will often refer to the terms “model” and “scenario”. For example, the 2014 model is a set of parameters $\{\alpha_i^{p2014}, \theta_j^{p2014}, \beta_i^{p2014}\}$. The scenario, in turn, is characterized

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.

by a set of hypothetical macro variables \mathbf{x}_{jt} . Note that the 2014 model is an estimate of the actual models that banks employed in the 2014 stress test. Similarly, the 2016 model is an estimate of the actual models that banks employed in the 2016 stress test. In this paper, we will refer to our estimates of banks’ underlying models simply as “model” or “models”.

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

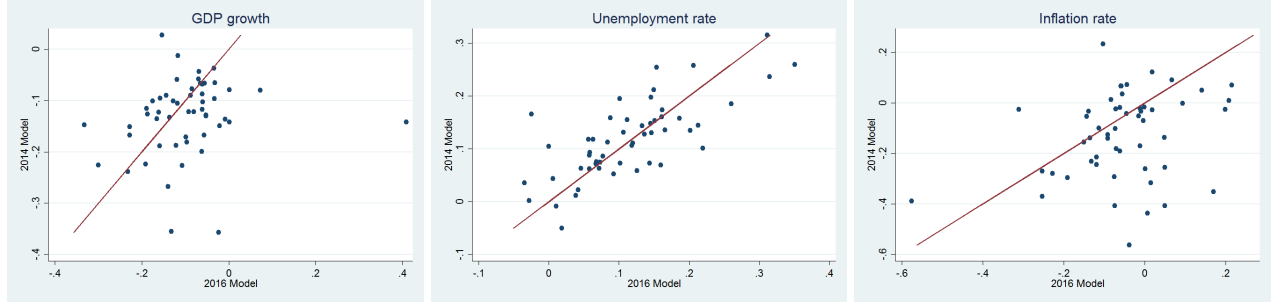
Weights on macro variables Results from the first-stage regressions are presented in figure 1. In each of the three panels, the country-specific coefficients $\hat{\theta}_j^p$ obtained from the 2014 data are plotted against those resulting from the 2016 data. The left (middle) panel shows the coefficients 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.

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 0.73 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 play an important role in explaining the data. In 2016, a slightly larger share of the variation

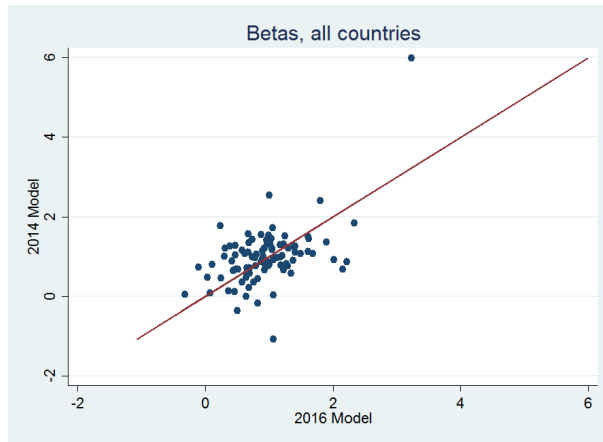
¹⁴We also estimated the 2014 model by including all banks for which information is available in the sample. All of the results presented in this paper continue to hold.

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.

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.

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:

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

where L_{it}^y represents the loan losses of bank i in year t derived from model $y \in \{2014, 2016\}$.¹⁷

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

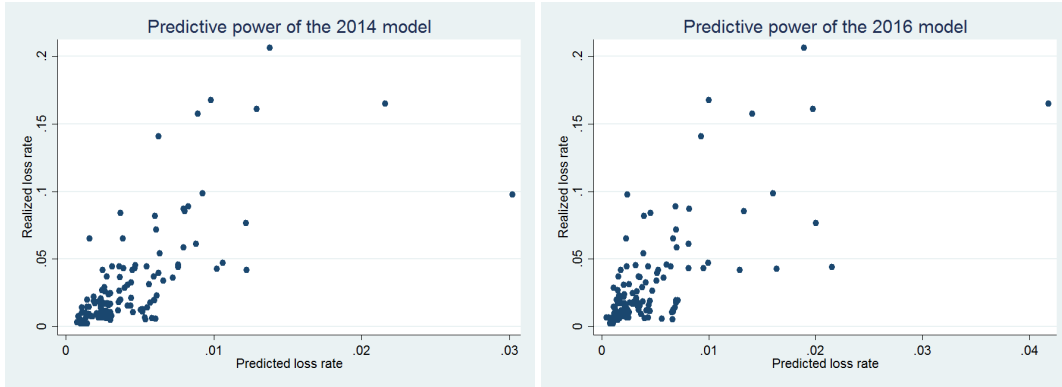
¹⁶Data on realized macroeconomic variables are from the World Bank's World Development Indicators.

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, 2016:Q2 exposures for 2016 loss rates. Data for 2014:Q4 and 2016:Q2 is from the transparency exercises that

Table 2: Model estimation results: R^2

	Corp	Retail
2016 stress test		
Observations	1,715	1,613
R^2	0.578	0.699
R^2 , no FE in 2nd step	0.477	0.421
2014 stress test		
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 round 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	2016 model
	(1)	(2)
R^2	0.484	0.504
Rank correlation	0.689	0.659
Sum of squared errors	0.25	0.24
Observations	129	129

Note: This table 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 loan loss reserves 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.

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 column (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

Four facts emerge from the losses shown in table 4. 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 the year the model was used.¹⁹

Fourth, 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^{p2014}), and 2016 fixed effects and bank sensitivities (β_j^{p2016}) 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.

Table 5: Explaining scenario changes

	(1) ΔS_i^{14}	(2) ΔS_i^{16}	(3) ΔS_i^{14}	(4) ΔS_i^{16}	(5) ΔS_i^{14}	(6) ΔS_i^{16}
Capital buffer	0.00157 (0.00142)	-0.00676 (0.00538)				
ΔE_i^{14}			0.202 (0.186)			
ΔE_i^{16}				0.337 (0.258)		
ΔRWD_i					-0.00578*** (0.00170)	-0.00613 (0.00511)
Constant	-0.0567 (0.0611)	-0.140 (0.140)	-0.00956 (0.0291)	-0.288*** (0.0825)	-0.0282 (0.0266)	-0.310*** (0.0820)
Observations	38	38	50	50	49	49
R-squared	0.033	0.039	0.088	0.041	0.288	0.046

Note: This table analyzes, at the bank-level, the relationship between scenario changes (ΔS_i^e), capital buffers, the change in losses that results from exposure changes (ΔE_i^e), and changes in risk-weight densities ΔRWD_i . Robust standard errors in parentheses in columns (1), (2), (5), (6). Bootstrapped standard errors in parentheses in columns (3) and (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2 Bank-level analysis

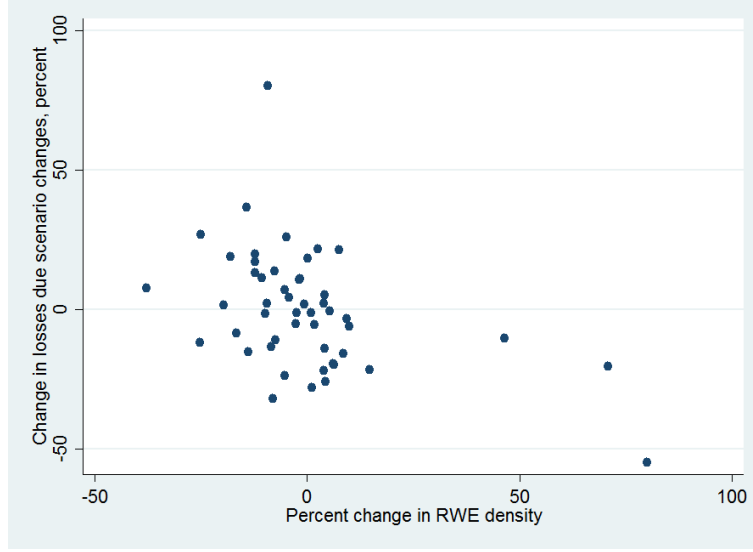
In the following, we investigate the various changes in credit losses further, focusing on losses in the adverse scenario. Instead of aggregating losses, we compute counterfactual losses for each bank. ΔM_i^e stands for the log change in losses of bank i stemming from model changes, keeping the scenario 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 scenario 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 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 columns (1) and (2) of table 5, scenario changes ΔS_i^e are regressed on banks' capital buffers. A bank's capital buffer is computed as its CET1 capital ratios as of 2015:Q4 minus its

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

Figure 4: Scenarios changes and changes in RWAs



Note: The figure plots scenario changes ΔS_i^{14} in percent against the percent change in banks' risk-weight densities from 2013:Q4 to 2015:Q4.

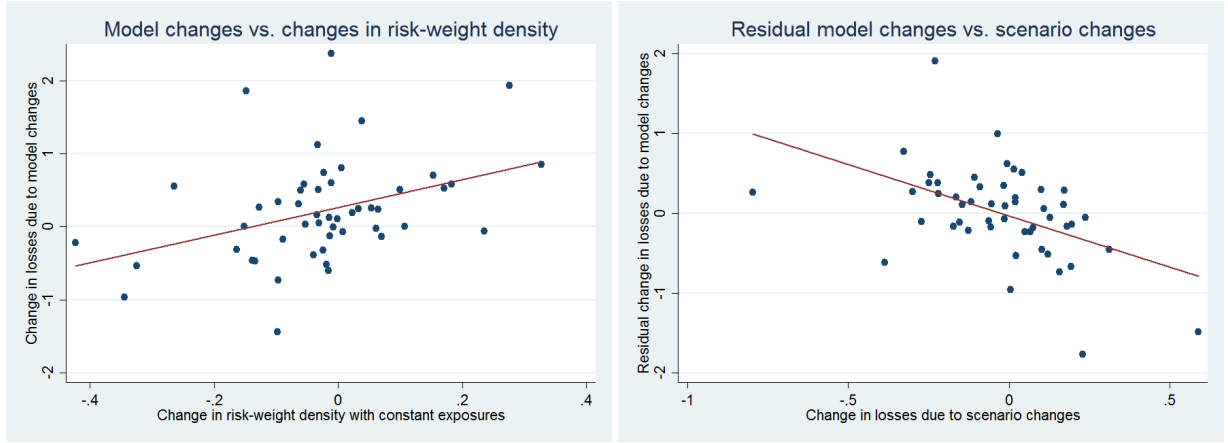
all-in regulatory capital requirement in 2016.²¹ Columns (1) and (2) indicate that there is no robust relationship between scenario changes and capital buffers. In this sense, scenarios are unbiased.

In column (3) and (4) of table 5, scenario changes ΔS^e are regressed on exposure changes ΔE^e . 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. Therefore, changes in losses from scenario changes did not offset changes in losses from changes in exposures. Interestingly, there is a strong negative association between scenario changes and changes in the riskiness of banks' portfolios, however, as the next paragraph explains.

Column (5) and (6) show regressions of scenario changes ΔS^e on the percent change in the ratio of banks' risk-weighted exposures to total exposures from 2013:Q4 to 2015:Q4. For the computation of a bank's risk-weight density, we divide a bank's total risk-weighted exposures for credit risk by its total credit exposures as of 2013:Q4 and 2015:Q4, respectively. The regression results suggest that changes in credit losses stemming from changes in the adverse scenario tended to reduce credit losses more for banks whose risk-weight densities increased

²¹The all-in regulatory capital requirement includes Pillar 1, Pillar 2, and additional buffer requirements, for example, the buffer for Global Systemically Important Banks (GSIBs).

Figure 5: Model changes, exposure and scenario changes, and changes in non-performing exposures



Note: The left panel plots model changes ΔM_i^{16} against the change in risk-weight densities given constant exposures from 2013:Q4 to 2015:Q4. The right panel in the figure plots residual model changes obtained as the errors of a regression of model changes ΔM_i^{16} on changes in risk-weight densities given constant exposures against the change in losses from scenario changes ΔS_i^{14} . The red lines show the linear relationships that result from simple linear regressions.

from 2013:Q4 to 2015:Q4. In other words, banks that increased the riskiness of their credit portfolios tended to see a 2016 adverse scenario that, for them, was less severe than that in 2014. In our view, the most likely explanation for the negative correlation is related to the fact that changes in scenarios are correlated with changes in countries' macroeconomic developments. As discussed, EBA scenarios are designed as a shock to the baseline. Thus countries with an improved macro economy tend to be subject to a less severe adverse scenario in absolute terms. As a country's macro economy improves, banks take on more risk. Figure 4 displays the relationship presented in column (4) of table 5 graphically.²²

Model changes Next, we study model changes by bank. Specifically, we investigate what factors can explain them. One key factor that should drive model changes are changes in the riskiness of the underlying portfolios. When a bank moves to safer borrowers, loss rates for a given scenario should be lower. The EBA stress test data contains risk-exposure amounts and exposures by bank i , country j , and portfolio p . To isolate the role of changes in risk within portfolios, we use these data and compute changes in banks' risk-weight densities for constant exposures. Specifically, we compute the risk-weight density RWD_{ijpT} for each bank i , country

²²One alternative explanation links the stress test scenarios directly to bank risk taking. If banks can predict scenarios, they might increase their risk-weighted asset density/risk in their portfolios when they anticipate stress tests to be less stringent.

j , and portfolio p at the jump-off point of the stress test T (2013:Q4 for the 2014 stress test and 2015:Q4 for the 2016 stress test). We then compute the weighted-average risk-weight density of bank i (RWD_i^*) by weighting each RWD_{ijpT} with the same weight $\omega_{icp} = \frac{\text{exposure}_{icp2013:Q4}}{\sum_j \sum_p \text{exposure}_{icp2013:Q4}}$ for each jump-off point.²³ We keep the weight constant to capture changes in riskiness within portfolios independent of changes in riskiness that come from a reallocation of exposures across portfolios. (Since our model projects loss rates at the bank-country-portfolio level, changes in exposures across portfolios should not lead to changes in model parameters per se.)

Table 6: Explaining model changes

	(1) ΔM_i^{16}	(2) ΔM_i^{16}	(3) ΔE_i^{14}	(4) ΔM_i^{16}	(5) ΔM_i^{16}
ΔRWD_i^*	1.686** (0.780)	1.495* (0.884)	-1.368** (0.510)	1.239 (0.812)	0.631 (0.756)
ΔE_i^{14}		-0.140 (0.492)		0.0778 (0.376)	
ΔS_i^{14}				-1.429*** (0.452)	
ΔES_i^{14}					-0.592* (0.309)
Constant	-0.0812 (0.0911)	-0.0971 (0.0928)	-0.114*** (0.0388)	-0.123 (0.0823)	-0.167* (0.0899)
Observations	50	50	50	50	50
R-squared	0.145	0.148	0.379	0.363	0.254

Note: This table investigates to what extent model changes M_i^e can be explained by changes in risk-weight densities RWD_i^* , scenario changes ΔS_i^{14} and exposure changes ΔE_i^{14} . RWD_i^* is computed as the change in the average ratio of risk-weighted exposures over total exposures of bank i from 2013:Q4 to 2015:Q4, assuming constant weights. Robust standard errors in parentheses in columns (1) and (3). Standard errors in other columns were bootstrapped. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (1) of table 6 indicates that changes in losses from model changes ΔM_i^{16} are positively correlated with changes in banks' risk-weight densities. As should be the case, banks whose average portfolio risk increased by more exhibit model changes that resulted in higher credit losses for the same exposures and adverse scenario. The R^2 of the regression is fairly high at 14.5 percent.²⁴ The left panel of figure 5 plots model changes against changes in risk-weight density given constant exposures for illustration.

In a next step, we ask how exposure changes relate to model changes. When exposure

²³Using weights based on 2015:Q4 exposures delivers very similar results.

²⁴We repeat the regressions shown in table 6 with ΔM_i^{14} as the dependent variable in table 10. Results are shown in the appendix and are very similar both qualitatively and quantitatively.

changes ΔE_i^{14} are included in the regression, the estimated effect of changes in a bank's risk-weight density becomes weaker. This is because exposure changes and changes in risk-weight densities given constant exposures are negatively correlated as column (3) shows. This is also as expected. When a bank's portfolio becomes riskier, the bank reshuffles and reduces exposures so as to offset the increase in risk.

We are also interested in the relationship of model changes ΔM_i^{16} with scenarios changes. Column (4) includes ΔS^{14} as an additional explanatory variable. The negative coefficient associated with scenario changes indicates that banks that would have seen a higher increase in losses because of changes to the adverse scenario in 2016, had adjustments to their models that brought down credit losses by more, controlling for effects of changes in the riskiness of portfolios. Note that the R^2 of the regression of model changes improves significantly, by more than 20 percentage points, when scenario changes are included in the estimation. The right panel of figure 5 highlights the strong negative relationship between scenario changes and model changes. It plots the residual from the regression shown in column (2) of table 6 against scenario changes ΔS^{14} . For robustness, column (5) of table 6 includes as explanatory variable the changes in credit losses stemming from changes in the scenario and changes in exposures combined, which produces the same result. We conclude that model adjustments effectively smoothed losses for banks across the stress tests. These adjustments were independent of observable changes in the riskiness of underlying portfolios.

The analysis so far has considered the relationship between model, scenario and exposure changes at the bank-level. However, we can also conduct the same analysis at the bank-country level. Table 7 presents results from running key regressions from table 6 on the more disaggregated data. Column (1) to (3) of table 7 confirm prior results on the predictive power of changes in risk-weight densities and scenario changes for model changes. The regression shown in column (4) includes two additional variables: a country's share in a bank's total exposures as well as an interaction term of this share with the change in losses due to scenario changes ΔS_{ij}^{14} . The coefficient on the interaction term is negative and significant at a 5-percent significance level, indicating that the same percentage change in credit losses because of scenario changes led to a bigger percentage reduction in losses due to model changes when the country portfolio was more important for the bank. This is precisely the relationship one would expect to see if model changes were made with the intent to affect a bank's aggregate credit losses.²⁵

In column (5), we test whether the relationship between scenario and model changes differs

²⁵We also checked whether the effect of scenario changes on model changes is bigger for home country exposures but the interaction term between a home country dummy and ΔS_{ij}^{14} was not significant at standard significance levels.

depending on whether the change in losses because of scenario changes is negative or positive. To this end, we create a dummy variable that takes a value of 1 if $\Delta S^{14} > 0$ and is 0 otherwise and interact it with ΔS^{14} . The coefficient on the interaction term is negative and statistically significant at a 10-percent level. Thus, scenario changes have a stronger association with model changes when they are positive, that is, when changes in the adverse scenario would have increased credit losses for a bank-country pair. This represents more evidence for systematic adjustments intended to contain credit losses for banks.

Table 7: Model changes at the bank-country-level

	(1) ΔM_i^{16}	(2) ΔM_i^{16}	(3) ΔM_i^{16}	(4) ΔM_i^{16}	(5) ΔM_i^{16}
ΔRWD_{ij}	0.166* (0.0991)	0.107 (0.106)	0.133 (0.0850)	0.138* (0.0811)	0.127 (0.0801)
ΔE_{ij}^{14}		-0.180** (0.0885)	-0.0277 (0.0859)	-0.0238 (0.0823)	-0.0427 (0.0787)
ΔS_{ij}^{14}			-0.842*** (0.0863)	-0.731*** (0.0931)	-0.362 (0.248)
exp. share _{ij} \times ΔS_{ij}^{14}				-1.162** (0.532)	-1.358*** (0.523)
exp. share _{ij}				0.175 (0.111)	0.140 (0.113)
Dummy _{ij} \times ΔS_{ij}^{14}					-0.516* (0.293)
Dummy _{ij}					0.000206 (0.0939)
Constant	-0.243*** (0.0373)	-0.251*** (0.0373)	-0.220*** (0.0314)	-0.257*** (0.0377)	-0.186** (0.0760)
Observations	257	257	257	257	257
R-squared	0.009	0.029	0.316	0.346	0.357

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table confirms results of table 6 based on bank-country level data. Column (4) investigates whether the reduction of credit losses through model changes is particularly strong for larger portfolios. Exp. share_{ij} stands for the share of country j in total exposures of bank i . Column (5) test for asymmetric effects of negative and positive changes in losses from scenario changes. Dummy_{ij} takes a value of 1 if $\Delta S_{ij}^{14} > 0$ and 0 otherwise. RWD_{ij} is computed as the percent change in the ratio of risk-weighted exposures over total exposures of bank i and in country j from 2013:Q4 to 2015:Q4. Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To understand how quantitatively relevant model changes between the stress tests are, we calculate the difference (m16/s16/e16-m14/s16/e16) for each bank as a ratio of its end-2015

CET1 capital. On average, the decrease in losses that came from model changes was 2.8 percent of a bank’s CET1 capital in the adverse scenario. Taking out the portion of changes in losses from model changes that can be attributed to changes in risk, model changes reduced losses for banks by an average of 1.7 percent of their CET1 capital in the adverse scenario. This number masks significant heterogeneity across banks, however. For the 10 banks with the largest reduction in credit losses from model changes (taking out the portion explained by model changes), the average reduction in credit losses was 15 percent of CET1 capital, which is economically significant.

6 Model Changes: Digging Deeper

This section further examines 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 amid less supervisory scrutiny.

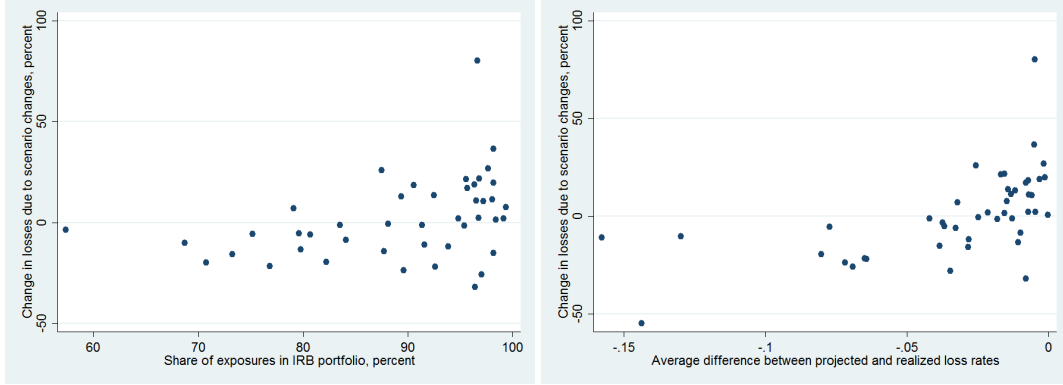
6.1 The role of the IRB approach and model performance

Previously, we showed that scenario changes were independent of bank capital buffers. However, the increase in losses from scenario 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 weight 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 8, ΔS_i^{14} is regressed on the share of a bank’s IRB exposures in total exposures.²⁶ The resulting regression coefficient is significant at the 5 percent level, indicating a positive relationship between scenario changes and the importance of the IRB approach at the bank level. This relationship, which is plotted in the left panel of figure 6, might have helped model adjustments because those banks that had more model flexibility had the biggest incentive to adjust the models.

Next, we analyze whether scenarios changes are correlated with model performance by bank.

²⁶The sample excludes banks with zero IRB exposures.

Figure 6: 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 scenario changes between stress test editions (ΔS_i^{14}) against the share of a bank's exposures subject to the internal risk based approach as of 2015:Q4. In the right panel ΔS_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 changes in this chart were computed as percent changes rather than log changes.

Model performance is judged using the methodology described in section 4.3. In column (2) of table 8, ΔS_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 7). 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 scenario changes. The right panel of figure 6 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 may have 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 8 present the results. Column (4) shows that banks with a higher share of exposures subject to the IRB approach indeed had model changes that resulted in a larger reduction in losses controlling for changes in a bank's risk-weight density under constant exposures. Column (5) indicates that also banks whose models under-predicted realized loss rates by less saw a larger decline in losses from model changes. Column (7) includes both factors in the regression together with risk-weight density changes, scenario and exposure changes. While the coefficients associated with banks' share of IRB exposures and model performance are not significant at the 10 percent level, the R^2 increases to 40 percent when these variables are included, up from 37.5 percent

Table 8: The role of the IRB approach and model performance, regressions

	(1) ΔS_i^{14}	(2) ΔS_i^{14}	(3) ΔS_i^{14}	(4) ΔM_i^{16}	(5) ΔM_i^{16}	(6) ΔM_i^{16}	(7) ΔM_i^{16}
ΔRWD_i^*	-0.352 (0.231)	-0.203 (0.180)	-0.296 (0.182)	1.544*** (0.482)	0.873* (0.450)	0.771 (0.796)	0.702 (0.782)
IRB share	0.00633** (0.00245)		0.00243 (0.00236)	-0.0176*** (0.00637)			-0.00937 (0.00990)
MP_i^{14}		3.502*** (1.157)	2.260** (0.877)		-5.262*** (1.386)		0.0249 (3.654)
ΔS_j^{14}						-1.459*** (0.555)	-1.322* (0.803)
ΔE_j^{14}						-0.283 (0.529)	-0.249 (0.642)
Constant	-0.576*** (0.208)	0.0929** (0.0383)	-0.148 (0.215)	1.427** (0.559)	-0.323*** (0.0977)	-0.167** (0.0720)	0.673 (0.910)
Observations	44	45	42	44	45	42	42
R-squared	0.179	0.394	0.310	0.234	0.205	0.375	0.398

Note: This table explores the correlation between scenario changes (ΔS_i^{14}), the share of a bank's exposures subject to the internal risk based approach, and its model performance (columns 1-3). It also investigates whether these two latter factors can explain the change in losses coming from model changes (columns 4-7). Robust standard errors in parentheses in columns (1) to (5). Bootstrapped standard errors in parentheses in columns (6) and (7). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

in column (6), indicating that they are somewhat relevant in explaining model changes even after controlling for banks' incentive to adjust models and changes in the risk of underlying portfolios.²⁷ At the same time, the regression shows that model changes remain strongly related to scenario changes even when controlling for the scope of improvements in model performance.

6.2 A closer look at changes in model performance

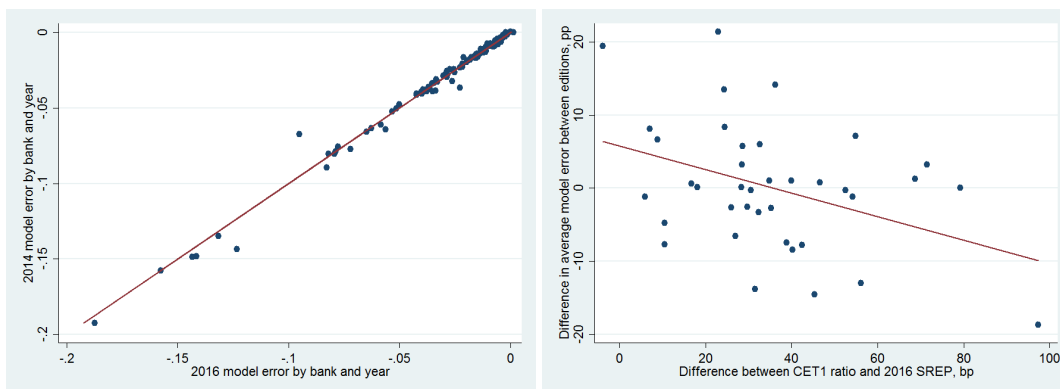
In a final step in this section, we study how model changes affected model performance by bank. As discussed in section 4.3, the overall performance of the models in explaining realized loss rates remained very similar across stress tests.

The left panel of figure 7 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.²⁸ Second, the performance of the models was relatively stable

²⁷The increase in the R^2 is stronger in table 11 where we repeat the regressions with ΔM_i^{14} as the dependent variable.

²⁸This fact can also be seen from figure 6.

Figure 7: 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 positive (negative) change indicates an improvement (deterioration) in model performance.

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 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 right panel of figure 7 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 an improvement (deterioration) in model performance. The negative 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.²⁹ This might indicate that banks with weaker capital buffers saw a stronger need to improve model performance, probably because supervisors paid greater attention to them.

To sum up, systematic model changes that effectively lowered credit losses were helped by several factors. First, banks who would have seen the strongest increase in losses had the biggest flexibility in modeling credit risk. Second, they had better models, meaning that their models

²⁹The 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.

may not have been 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 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.³⁰

7 The Market Response to the 2016 Stress Test Results

As we document, only a portion of the observed model changes can be explained by changes in the riskiness of bank portfolios. Another portion is likely explained by banks' incentive to bring credit losses down when faced with a more severe adverse scenario. 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 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.³¹ 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} .³² Bank stock prices are available for 33 of the 51 banks (as not all banks are public).³³ 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 8 plots abnormal changes in stock prices against residual model changes (those that cannot be explained by changes in risk-weight densities given constant exposures). The chart suggests that bank equity investors earned higher abnormal returns the smaller the residual increase in losses from model changes was. In other words, banks that

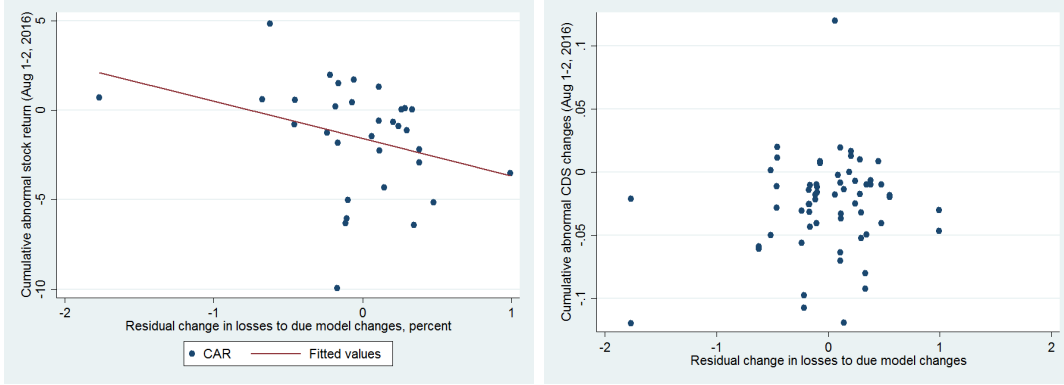
³⁰The projections that are made public are approved by the supervisors that oversee the stress tests. These projections may reflect adjustments by the supervisors and, therefore, may differ from the banks' original projections that follow directly from the banks' own models. In this context, Colliard (forthcoming) argues that even when risk models are audited by supervisors, models can be biased in equilibrium.

³¹Each 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.

³²We 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.

³³We exclude one outlier from the regressions shown in table 9, which reduces the number of banks to 32.

Figure 8: 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 the residual of a regression of ΔM_i^{16} on ΔRWD_i^* , excluding one outlier bank. The right panel plots cumulative abnormal changes in banks' CDS spreads over the same days against the same residuals.

reduced credit losses through model changes more experienced higher abnormal returns. A correlation between abnormal changes in CDS spreads and model changes is not immediately apparent from the right panel of figure 8, which has residual model changes on the x-axis and abnormal changes in the spreads on the y-axis. However, multivariate regression analysis reveals a negative systematic relationship that depends on banks' capital buffers.

Before turning to CDS spreads, consider columns (1) through (3) of table 9. The econometric evidence suggests the biggest predictive power for model changes consistent with the left panel of figure 8. The associated coefficient for model changes ΔM_i^{16} in column (3) is significant at a 5-percent level, and the R^2 of the regression is by far the highest among columns (1) to (3). The coefficient in column (3) implies that a 10 percent decline in credit losses, led to a 0.2 percentage point higher return. Scenario changes itself are not significant for abnormal stock returns (see column 2).

Columns (4) through (7) repeat the exercise for abnormal changes in CDS spreads. The regression shown in column (7) 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 associated with model changes turn significant at a 12-percent level with slightly higher significance of the interaction term. Based on the coefficients in column (7), a bank with a 30 percent capital buffer would see an increase in its CDS spread by 9 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 prices 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 only 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 9: Model changes and abnormal changes in stock prices and CDS spreads, regressions

	stock prices			CDS spreads			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta Total_i$	-1.607 (1.211)			0.0180 (0.0117)			
ΔS_i^{14}		2.490 (3.182)			0.0504* (0.0288)		
ΔM_i^{16}			-2.055** (1.032)			0.0135 (0.0121)	-0.0435 (0.0285)
ΔRWD^*_i			-0.733 (3.744)			-0.0296 (0.0388)	0.00917 (0.0378)
Capital buffer							0.000632 (0.000454)
$\Delta M_i^{16} \times \text{cap buf}$							0.00148* (0.000893)
Constant	-1.922*** (0.512)	-1.397*** (0.503)	-1.891*** (0.533)	-0.0223*** (0.00538)	-0.0243*** (0.00518)	-0.0250*** (0.00513)	-0.0397*** (0.0131)
Observations	32	32	32	61	61	61	57
R-squared	0.061	0.033	0.127	0.046	0.047	0.029	0.092

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 (3) is the cumulative abnormal stock return on August 1 and 2, 2017. The dependent variable in columns (4) to (7) 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. Bootstrapped 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 suggests that the flexibility that exists in the design and use of banks' own models is systematically exploited to minimize projected losses in stress tests.³⁴ 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 and can prevent banks from modeling their stress away.

³⁴See, for example, Plosser and Santos (2014), Behn et al. (2016), and Acharya et al. (2014).

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Appendix Tables

Table 10: Robustness I

VARIABLES	(1) ΔM_i^{14}	(2) ΔM_i^{14}	(3) ΔM_i^{14}	(4) ΔM_i^{14}
ΔRWD_i^*	1.892*** (0.602)	1.062 (0.820)	0.866 (0.778)	0.599 (0.788)
ΔE_i^{14}		-0.607 (0.485)	-0.440 (0.508)	
ΔS_i^{14}			-1.090** (0.505)	
ΔES_i^{14}				-0.725** (0.337)
Constant	0.266*** (0.0932)	0.197** (0.0898)	0.178** (0.0859)	0.161* (0.0858)
Observations	50	50	50	50
R-squared	0.145	0.190	0.290	0.276

Note: This table replicates some of the results from table 6 using ΔM^{14} instead of ΔM^{16} as the dependent variable. Robust standard errors in parentheses in column (1). Bootstrapped standard errors in the other columns. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Robustness II

VARIABLES	(1) ΔM_i^{14}	(2) ΔM_i^{14}	(3) ΔM_i^{14}	(4) ΔM_i^{14}
ΔRWD_i^*	1.389** (0.682)	1.000 (0.721)	-0.0304 (1.279)	-0.217 (1.154)
IRB share	-0.0256** (0.0110)			-0.0154 (0.0132)
MP_i^{14}		-7.674** (3.674)		-5.014 (5.159)
ΔS_i^{14}			-1.373** (0.666)	-0.729 (0.880)
ΔE_i^{14}			-0.935 (1.076)	-0.745 (0.904)
Constant	2.497** (1.001)	-0.0187 (0.121)	0.158 (0.0975)	1.381 (1.208)
Observations	44	45	42	42
R-squared	0.215	0.247	0.274	0.378

Note: This table replicates some of the results from table 8 using ΔM^{14} instead of ΔM^{16} as the dependent variable. Robust standard errors in parentheses in columns (1) and (2). Bootstrapped standard errors in the other columns. *** p<0.01, ** p<0.05, * p<0.1.