OFFICE OF FINANCIAL RESEARCH
OFR WORKING PAPER

15-02 | March 3, 2015

Are the Federal Reserve's Stress Test Results Predictable?

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Paul Glasserman* and Gowtham Tangirala†

Abstract

Regulatory stress tests have become a key tool for setting bank capital levels. Publicly disclosed results for four rounds of stress tests suggest that as the stress testing process has evolved, its outcomes have become more predictable and therefore arguably less informative. In particular, projected stress losses in the 2013 and 2014 stress tests are nearly perfectly correlated for bank holding companies that participated in both rounds. We also compare projected losses across different scenarios used in the 2014 stress test and find surprisingly high correlations for outcomes grouped by bank or by loan category, which suggests an opportunity to get more information out of the stress tests through greater diversity in the scenarios used. We discuss potential implications of these patterns for the further development and application of stress testing.

Regulatory stress tests have become a central tool for enhancing the resilience of the banking system. The current era of stress testing began with the 2009 Supervisory Capital Assessment Program (SCAP), which played an important role in turning around the financial crisis in the United States. The SCAP tested the ability of the largest U.S. bank holding companies to withstand a further worsening of economic conditions, and it combined this test with a government backstop for banks needing additional capital. In a major departure from customary supervisory practice, results of the SCAP were made public. The release of this information is credited with helping to restore market confidence by reducing uncertainty about the state of the financial system and by making the government's response transparent. See Hirtle, Schuermann, and Stiroh [14] for further discussion of the SCAP's information content and its importance to the program.

The success of stress testing in the SCAP led to the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) and the Dodd-Frank Act Stress Testing (DFAST) program, named for the Dodd-Frank Wall Street Reform and Consumer Protection Act. We will provide background on these programs in the next section, but their supervisory stress testing components are broadly similar to the SCAP's. The Federal Reserve defines a small number of

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scenarios through economic and financial variables, and the banks and their supervisors evaluate bank losses resulting from these scenarios. In several but not all cases, summary information on stress losses by bank and asset category have then been made public.

The results of these stress tests are pivotal in setting bank capital levels and allowed distributions to shareholders. Stress testing has overshadowed the use of internal bank models to calculate risk-weighted assets, which was the trend in capital requirements for the largest banks prior to the financial crisis. The annual execution of the CCAR/DFAST process has become an enormous undertaking for the banks covered by these programs and their supervisors.

Despite the complexity of this process, using results made public across various stress tests we find that projected losses by bank and loan category are fairly predictable and are becoming increasingly so. In particular, losses for CCAR 2013 and 2014 are nearly perfectly correlated for banks that participated both years. Most of this article documents these findings.

That stress losses would become predictable from one year to the next should not be surprising. If a bank's portfolio and the Federal Reserve's scenarios remain reasonably consistent over time, so should the bank's stress test results. In its first year of participation in the stress tests, a bank needs to make major investments in staff and information technology; over time, the process matures and becomes more routine. Indeed, consulting firms and software vendors have made a business of trying to simplify and standardize the stress testing process for banks to make it more routine. The models used by the Federal Reserve to define scenarios and project losses have also been refined and should change less over time. Banks have incentives to avoid investments that will attract high capital requirements through the stress tests. As discussed in Schuermann [17], they also face incentives to align their internal risk assessments with the Federal Reserve's. All of these factors contribute to making outcomes more predictable over time.

But whereas the results of stress tests may be predictable, the results of actual shocks to the financial system are not, and herein lies the concern. The process of maturation that makes stress test results more predictable may also make the stress tests less effective. We should be careful in extrapolating from the early success of the SCAP and its immediate successors to assume that the same process will continue to be effective in the future. The SCAP worked, in part, by providing new information. To the extent that stress test results become more predictable, they become less informative.

Several authors including Acharya, Engle, and Pierret [1], Covas, Lump, and Zakrajsek [8], Guerrieri and Welch [11], Hirtle et al. [13], and Kapinos and Mitnik [15], have developed models for bank stress testing using public data. These models seek to forecast bank vulnerability as an alternative or complement to supervisory stress tests. Our focus is different: we are interested in the predictability of the outcomes of the supervisory stress tests themselves, rather than in more accurate forecasting of bank vulnerability. Hirtle et al. [13] find significant correlation between their forecasts and DFAST outcomes, consistent with the predictability of the outcomes.

One way to reduce predictability is to increase the number and diversity of scenarios evaluated in a stress test. We compare results for the two stress scenarios used in DFAST 2014 and find an oddly high degree of correlation across scenarios by bank and by loan category. This pattern is particularly surprising given the large number of variables used to define the scenarios. The pattern suggests a missed opportunity to diversify the types of stresses tested.

The next section provides additional background on supervisory stress tests. We then compare the results for the two DFAST 2014 stress scenarios. The next two sections compare predictability across time, first for loss levels and then for loss rates. We then examine the stock market reaction to announcements of stress test results; consistent with the predictability of the results, we find no significant correlation between the severity of a bank's reported stress losses and the change in its stock price relative to the market. We conclude the paper with comments on how the limitations of predictable stress tests might be countered.

Background on Supervisory Bank Stress Tests

Our analysis draws on results from four rounds of stress tests: SCAP 2009, CCAR 2012, DFAST 2013, and DFAST 2014. For background, we review the essential features of these programs.

SCAP

The SCAP was launched in February 2009 and its results announced that May. It had the following features:

- *Scope:* The program applied to the 19 largest U.S. bank holding companies (BHCs): American Express Company, Bank of America Corporation, Bank of New York Mellon Corporation, BB&T Corporation, Capital One Financial Corporation, Citigroup Inc., Fifth Third Bancorp, The Goldman Sachs Group, Inc., GMAC LLC, JPMorgan Chase & Co., KeyCorp, MetLife, Inc., Morgan Stanley, The PNC Financial Services Group, Inc., Regions Financial Corporation, State Street Corporation, SunTrust Banks, Inc., U.S. Bancorp, and Wells Fargo & Company. MetLife exited banking in 2013 and has not been covered by the bank stress tests since then. The remaining group of 18 are the common participants across all rounds of stress tests. GMAC changed its name to Ally Financial Inc., after the SCAP.

- *Scenarios:* The SCAP used a baseline scenario and a more adverse scenario defined through a two-year decline in GDP and house prices and an increase in unemployment. A separate market shock similar to the second half of 2008 was applied to trading portfolios.
- *Asset categories:* Projected losses were calculated for five loan categories: first-lien mortgages, junior-lien mortgages, commercial and industrial (C&I) loans, commercial real estate (CRE) loans, and credit cards. Projected losses were calculated for banks' securities portfolios and for the trading portfolios of the five banks with large trading positions.
- *Disclosure:* Projected loss amounts and loss rates under the more adverse scenario were disclosed by asset category for each bank in Board of Governors [2].

The SCAP report also disclosed projected capital levels by bank, but we focus exclusively on projected losses.

CCAR

There was no supervisory stress test in 2010. CCAR, launched in 2011, differed from the SCAP in putting greater emphasis on the capital planning process and on the robustness of the processes employed by the participating BHCs in their internal risk management; see Board of Governors [3]. We focus exclusively on the stress testing component of the review.

CCAR 2011 applied to the same bank holding companies as the SCAP. The adverse scenario was enriched to specify a path of the economy over nine quarters for nine economic and financial variables. The scenario was made public, but no bank-specific results were disclosed. CCAR 2011 is therefore not part of our analysis.

CCAR 2012 again applied to the same 19 bank holding companies as the SCAP. The Federal Reserve's adverse scenario was further expanded to define paths for 25 variables, including more international factors. The loan categories were expanded to include consumer loans and a category called Other Loans. Projected stress losses were disclosed by bank and category under the Federal Reserve's adverse scenario. Banks were also required to define their own scenarios and estimate stress losses in these scenarios, but those results were not made public. Subsequent CCAR rounds have used DFAST stress test results, which we discuss next.

DFAST

The Dodd-Frank Act, passed by Congress in July 2010, includes requirements for annual regulatory stress tests, commonly referred to as DFAST. The act requires at least three scenarios

— a baseline, an adverse scenario, and a severely adverse scenario.

DFAST 2013 applied to the same bank holding companies as the SCAP, except for MetLife. DFAST 2014 covered all bank holding companies with over $50 billion in consolidated assets, bringing the number of reporting BHCs to 30. The group may continue to grow because the Dodd-Frank Act's stress testing provisions apply to all banks (and certain other financial companies) with over $10 billion in consolidated assets.

In DFAST 2013, results were disclosed for the severely adverse scenario only. DFAST 2014 disclosed results for both the adverse and severely adverse scenarios. We will compare results for the two scenarios in the next section.

Projected losses under DFAST are used as inputs to the CCAR capital planning process, so the two programs operate in parallel. DFAST provides public information on the capital strength of large banks, but CCAR is much more comprehensive and determines a large bank's ability to pay dividends or repurchase shares. We focus on the results of the stress tests.

DFAST requires banks to run and disclose two types of stress tests, in addition to the results calculated and reported by supervisors. Banks must disclose their own loss projections under the Federal Reserve's scenarios, and they are also required to run mid-cycle stress tests using their own scenarios and loss projections. See Hirtle, Kovner, and McKay [12] for a comparison of the Federal Reserve's and bank's results for the Federal Reserve's scenarios. We will use only the annual supervisory results in our analysis; we expect that the mid-cycle disclosures by individual companies would only enhance the predictability of the supervisory tests.

Data

We compiled data on projected loss amounts and loss rates by bank and by loan category from the Federal Reserve's reports Board of Governors [2, 4, 5, 6]. Figures 1 and 2 report summary statistics on projected losses (in billions of dollars) and loss rates (in percent), respectively.

We focus primarily on projected losses on loans. Trading and counterparty shocks apply only to a subset of the participating bank holding companies, and this part of the stress test operates differently from the rest of the program. The details of the market shock were not made public prior to 2013.

Figure 3 compares the loss rate distributions across the SCAP, CCAR 2012, and DFAST 2013 and 2014. For each histogram, we pool loss rates for all loan categories and all banks. The distributions for the three most recent rounds are similar to each other, consistent with the view that the overall process has stabilized over time. For illustration, we have superimposed

Year	Category	Mean	Median	Std Dev	Min	Max
	First Liens	7.3	1.9	10.4	0.1	32.4
	Junior Liens	6.4	1.7	7.8	0.6	21.4
2009	C&I	3.5	1.5	4.6	0.0	15.7
	CRE	3.3	2.9	2.7	0.2	9.4
	Credit Cards	6.9	3.2	8.4	0.0	21.2
	All Loans	32.8	12.6	41.6	5.4	136.6
	First Liens	3.8	1.5	5.6	0.0	17.7
	Junior Liens	3.5	1.2	5.1	0.0	16.0
	C&I	3.7	1.9	4.5	0.0	12.3
2012	CRE	1.4	0.8	1.7	0.0	6.7
	Credit Cards	7.1	3.2	9.1	0.1	27.0
	Other Consumer	1.4	0.6	2.1	0.0	8.1
	Other Loans	0.9	0.3	1.3	0.0	4.8
	All Loans	18.9	7.2	24.8	0.3	70.1
	First Liens	3.8	1.2	5.5	0.0	15.3
	Junior Liens	2.3	1.0	3.1	0.0	9.4
	C&I	3.4	1.7	3.5	0.0	11.1
2013	CRE	1.9	0.9	2.5	0.0	9.6
	Credit Cards	6.7	3.2	8.0	0.1	23.3
	Other Consumer	1.5	0.6	1.9	0.0	6.5
	Other Loans	0.7	0.3	0.8	0.0	2.9
	All Loans	17.6	6.7	21.3	0.3	57.5
	First Liens	3.2	0.9	5.0	0.0	15.7
	Junior Liens	2.4	0.8	3.5	0.0	9.9
	C&I	3.1	1.5	3.2	0.0	9.4
2014	CRE	2.2	1.1	2.6	0.0	9.4
	Credit Cards	6.5	2.8	8.0	0.1	24.8
	Other Consumer	1.5	0.7	1.8	0.0	6.1
	Other Loans	1.1	0.4	1.7	0.0	5.8
	All Loans	17.4	5.5	21.4	0.5	55.5

Figure 1: Summary statistics for loss levels (in billions of dollars) across loan categories and stress tests.

Year	Category	Mean	Median	Std Dev	Min	Max
2009	First Liens	7.7	8.1	2.8	3.4	11.9
	Junior Liens	13.2	13.2	4.6	6.3	21.2
	C&I	6.8	5.8	4.8	1.2	22.8
	CRE	15.2	10.9	11.9	5.5	45.2
	Credit Cards	22.6	22.3	5.4	17.4	37.9
	All Loans	7.9	8.7	3.7	0.4	14.3
2012	First Liens	6.3	7.1	2.8	0.0	9.5
	Junior Liens	12.5	12.1	3.3	7.8	21.1
	C&I	6.5	7.4	3.2	0.0	10.9
	CRE	6.5	5.6	4.3	2.1	20.1
	Credit Cards	17.7	18.5	3.4	10.0	22.4
	Other Consumer	5.3	3.7	5.3	0.0	23.4
	Other Loans	2.4	2.5	1.3	0.0	4.7
	All Loans	6.5	7.3	3.2	0.9	11.4
2013	First Liens	6.1	6.3	2.6	0.6	10.3
	Junior Liens	10.3	9.7	3.6	6.1	21.1
	C&I	8.8	6.5	10.5	0.0	49.8
	CRE	8.7	8.0	2.9	4.8	18.3
	Credit Cards	17.2	17.3	2.8	12.0	22.2
	Other Consumer	5.0	4.1	4.2	0.0	16.5
	Other Loans	2.1	1.8	0.9	0.8	4.5
	All Loans	6.6	6.7	2.8	2.0	13.2
2014	First Liens	4.6	4.9	2.0	1.0	7.5
	Junior Liens	9.0	9.9	2.7	4.8	13.5
	C&I	6.2	5.4	2.2	3.8	11.4
	CRE	9.5	8.9	4.7	4.8	26.2
	Credit Cards	15.6	16.2	2.7	10.6	20.5
	Other Consumer	4.5	3.9	3.6	0.0	14.0
	Other Loans	2.6	2.6	1.0	1.0	4.5
	All Loans	5.9	5.4	2.6	1.6	11.8

Figure 2: Summary statistics for loss rates (in percent) across loan categories and stress tests.

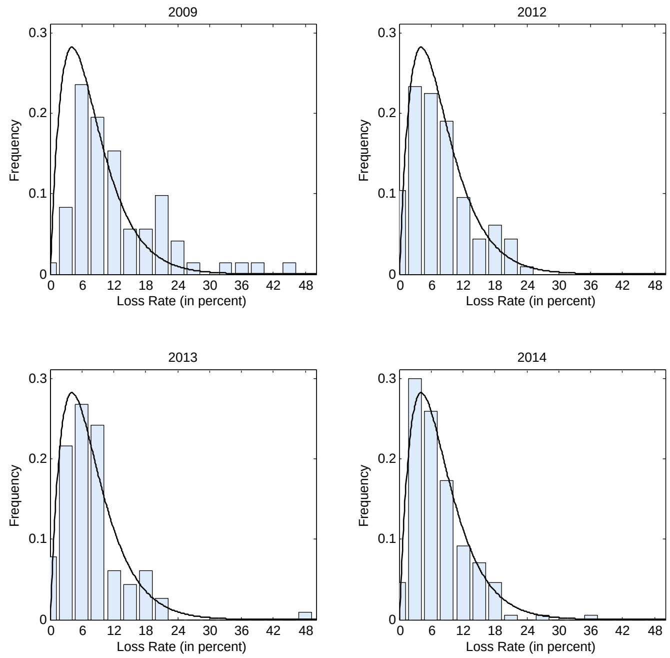


Figure 3: Distribution of loss rates across all loan categories and all banks in each of the four stress tests. The distributions for 2012–14 are not statistically significantly different from each other. The continuous curve in the figures is a gamma density estimated from the 2012–14 data.

on the histograms a probability density estimated from the 2012–14 data.[1] The consistency in the distributions is surprising given the increasing complexity of the underlying stress scenarios and the expansion in the number of participating banks in 2014.

Comparison Across Scenarios

As we noted earlier, DFAST 2014 was the first stress test to disclose loss projections for both an adverse and severely adverse scenario. Before investigating predictability across time, we compare results from the two scenarios.

Figure 4 shows results for the 30 BHCs that participated in DFAST 2014. For each BHC, we plot the severely adverse loss rate on the vertical scale and the adverse loss rate on the horizontal scale. Loss rates are measured in percent. In most cases, this gives us seven data points for each bank, corresponding to the seven loan categories used to report loss projections. Some banks have little or no lending in some categories, resulting in fewer than seven points.

[1] Two-sample Kolmogorov-Smirnov tests indicate no statistically significant difference between any two of the last three distributions, and each of the last three is statistically significantly different from the SCAP distribution. We fit a gamma distribution with shape parameter 2.1 and scale parameter 3.7 to the 2012–14 data. The density is multiplied by three in the charts for ease of comparison.

The results are striking. Across all 30 banks, we see a nearly perfect linear relationship between the losses in the two scenarios. This visual impression is quantified in Figure 6, which shows the results of bank-specific regressions of the form

$$SevereLossRate_{b,c} = \text{Intercept}_b + \text{Slope}_b \times AdverseLossRate_{b,c}, \tag{1}$$

where the intercept and slope depend on the bank b but not on the loan category c. The average R^2 across the 30 BHCs is 0.96. The slopes vary by bank but are mostly between 1.1 and 1.3. Few of the intercepts are significantly different from zero.

To put these patterns in perspective, consider that each scenario in DFAST 2014 is defined by the paths over nine quarters of 28 economic variables, so each scenario is a $9 \times 28 = 252$ dimensional object. This leaves a lot of room for differences across scenarios. We might expect different loan categories to respond differently to two such scenarios, given the complexity of the model. Yet the results say otherwise. Consider Bank of America, for example. The results say that its projected losses across all seven loan categories are a little more than 25 percent worse in one scenario than the other, effectively reducing stress severity to a single dimension.

Figure 5 shows corresponding results grouped by asset category and pooled across banks. For the seven loan categories, we show loss rates rather than dollar losses to put BHCs of different sizes on a consistent scale. In the lower right panel of the chart, we have included trading and counterparty losses. These are reported in billions of dollars because the Federal Reserve does not report rates for this category. Only eight of the 18 BHCs participate in this part of the stress test, and these are all among the largest BHCs, so size discrepancy is less of a concern in this category.

Again, we see a striking linear relationship between the two scenarios across all categories. The corresponding regression is now

$$SevereLossRate_{b,c} = \text{Intercept}_c + \text{Slope}_c \times AdverseLossRate_{b,c}, \tag{2}$$

with coefficients that depend on the loan category c but not the bank b. Figure 7 quantifies the pattern in the scatter plots. The results are surprising, even given the results of Figure 4: because the banks have different slopes and intercepts, there is no reason to expect that pooling the bank-specific linear relationships would produce category-specific linear relationships in loss rates.[2]

These patterns are puzzling. We would expect to see a more complex relationship between adverse and severely adverse outcomes, reflecting a nonlinear response of bank portfolios to

[2]Similar patterns apply to pre-provision net revenue and pre-tax net income measured as a percent of average assets, with correlations of 0.99 and 0.91, respectively, across the two scenarios.

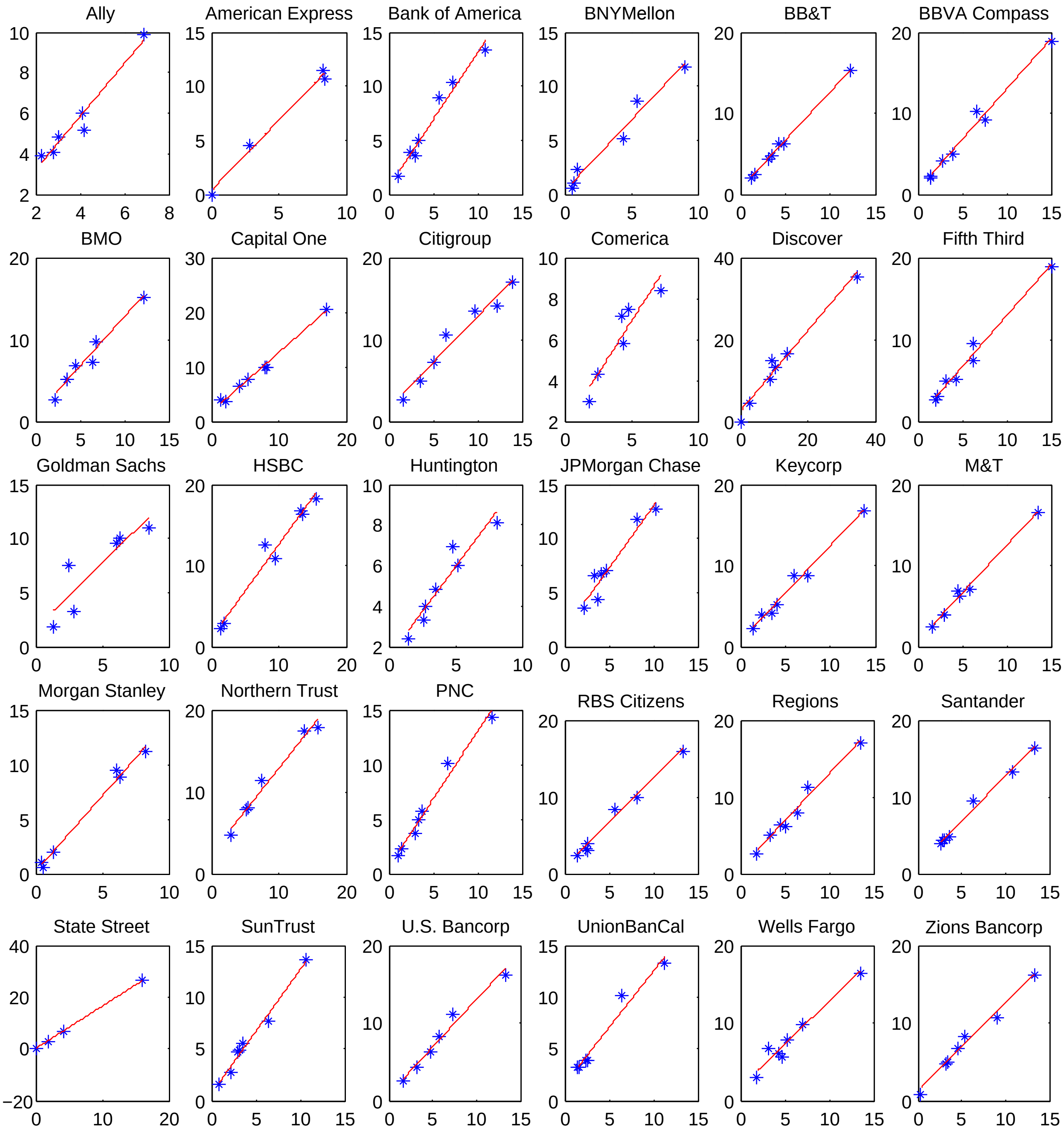


Figure 4: The plot for each BHC shows the severely adverse loss rate on the vertical scale and the adverse loss rate on the horizontal scale. Loss rates are in percent. Values shown are for DFAST 2014.

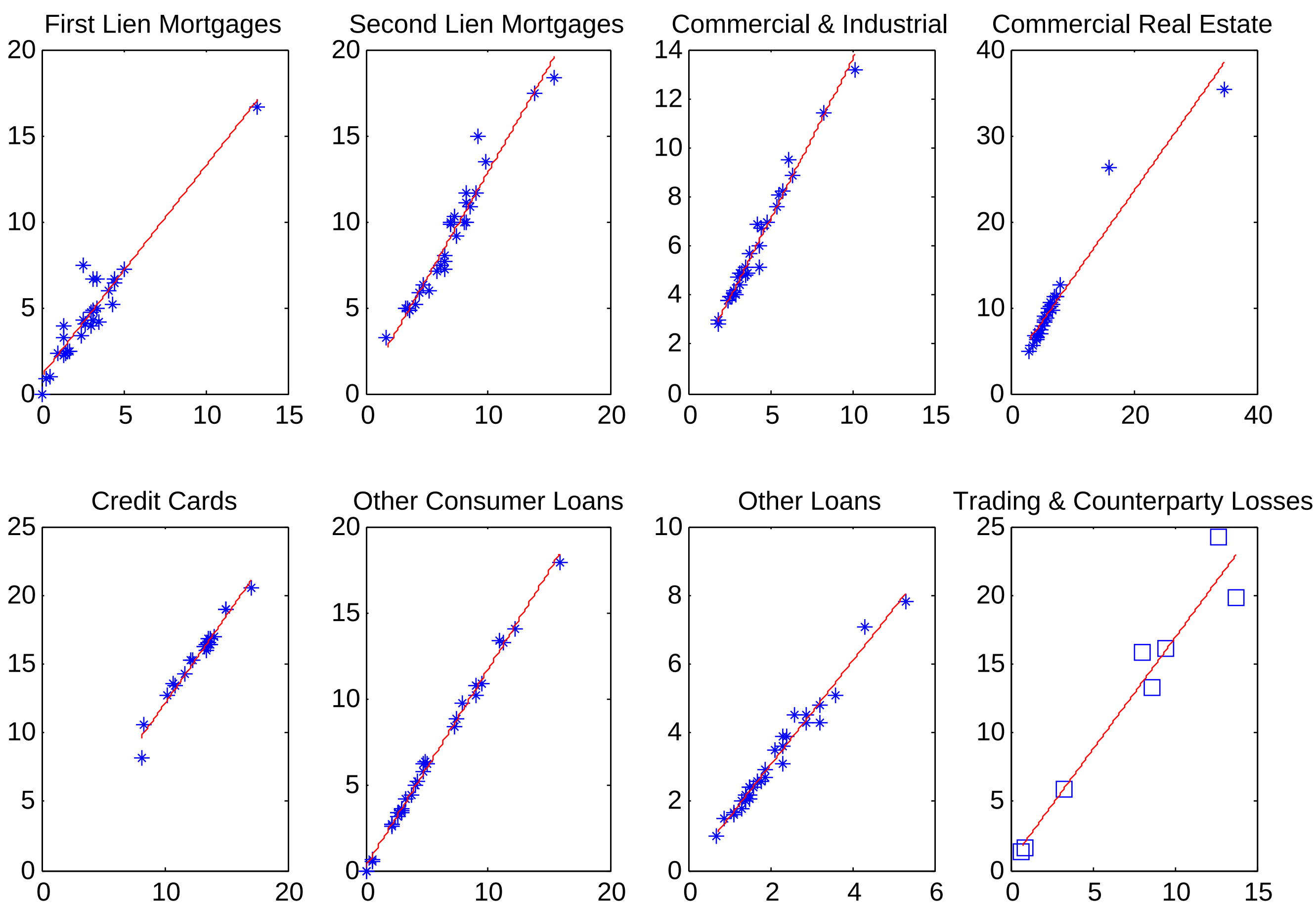


Figure 5: The plot for each loan category shows the severely adverse loss rate on the vertical scale and the adverse loss rate on the horizontal scale. Loss rates are in percent. Trading and counterparty losses are in billions of dollars. Values shown are for DFAST 2014.

Bank Holding Company	Slope_b	Intercept_b	R^2
Ally Financial Inc.	1.31***	0.56	0.96
American Express Company	1.25**	0.33	0.96
Bank of America Corporation	1.25***	0.65	0.97
The Bank of New York Mellon Corporation	1.31***	0.25	0.97
BB&T Corporation	1.19***	0.62**	1.00
BBVA Compass Bancshares, Inc.	1.24***	0.50	0.99
BMO Financial Corp.	1.20***	0.66	0.97
Capital One Financial Corporation	1.08***	1.63***	0.99
Citigroup Inc.	1.12***	1.48	0.96
Comerica Incorporated	1.02***	1.74	0.87
Discover Financial Services	0.98***	2.35*	0.97
Fifth Third Bancorp	1.25***	0.34	0.99
The Goldman Sachs Group, Inc.	1.21**	1.62	0.79
HSBC North America Holdings Inc.	1.15***	1.05	0.97
Huntington Banchsares Incorporated	0.89***	1.48**	0.91
JPMorgan Chase & Co.	1.15***	1.49	0.93
KeyCorp	1.18***	0.60	0.98
M&T Bank Corporation	1.18***	0.62*	0.99
Morgan Stanley	1.39***	0.12	0.99
Northern Trust Corporation	1.04***	2.37**	0.98
The PNC Financial Services Group, Inc.	1.24***	0.62	0.98
RBS Citizens Financial Group, Inc.	1.16***	0.73	0.99
Regions Financial Corporation	1.23***	0.61	0.98
Santander Holdings USA, Inc.	1.16***	0.94*	0.99
State Street Corporation	1.64***	-0.13	1.00
SunTrust Banks, Inc.	1.20***	0.66	0.98
U.S. Bancorp	1.22***	0.69	0.97
UnionBanCal Corporation	1.09***	1.57**	0.97
Wells Fargo & Company	1.11***	1.62*	0.96
Zions Bancorporation	1.14***	1.12*	0.98

Figure 6: Results of regression (1) by bank holding company of DFAST 2014 severely adverse loss rates versus adverse loss rates. Asterisks indicate statistical significance at the 10% level (*), 5% level (**), and 1% level (***).

economic shocks. The patterns appear to be an artifact of the stress testing process rather than an accurate reflection of potential bank losses. They suggest an opportunity to get more information out of the stress tests through greater diversity in the scenarios used.

In what follows, we confine ourselves to the predictability of stress losses in the severely adverse scenario; recall that 2014 is the only year for which we have results for two stress scenarios.

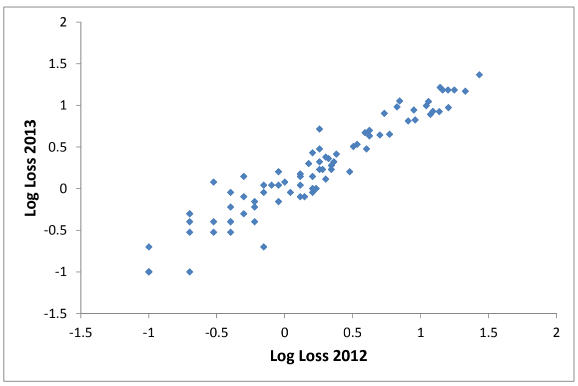
Predictability in Loss Levels

In this section, we examine the relationship between the projected losses S_T and S_{T-1} from stress tests run in years T and $T-1$, respectively. To do so, we need to limit ourselves to the 18 BHCs that participated in the stress tests of 2012–14.

Figure 8 compares losses across all banks and all loan categories except Other Loans from 2012 to 2013 and from 2013 to 2014. Because the BHCs vary widely in size, we take logarithms

Category	Slope$_c$	Intercept$_c$	R^2
First Liens	1.22***	0.98***	0.90
Junior Liens	1.23***	0.51	0.95
C &I	1.30***	0.58***	0.98
CRE	1.02***	3.07***	0.94
Credit Cards	1.28***	-0.71	0.97
Other Consumer	1.14***	0.21**	1.00
Other Loans	1.51***	0.02	0.97
All Loans	1.15***	1.08***	0.96

Figure 7: Results of regression (2) by loan category of DFAST 2014 severely adverse loss rates versus adverse loss rates. Asterisks indicate statistical significance at the 10% level (*), 5% level (**), and 1% level (***).



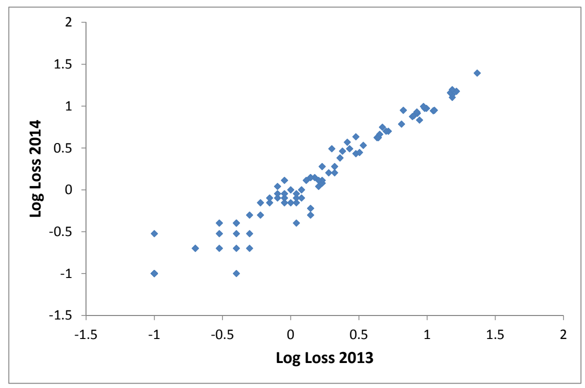


Figure 8: The charts show projected $\log_{10}$ losses in consecutive years across all banks and all loan categories except Other Loans. The left chart plots results for DFAST 2013 against CCAR 2012, and the right charge plots DFAST 2014 against DFAST 2013. The correlation is very high in both cases. Losses are in billions of dollars so a $\log_{10}$ value of 1 corresponds to a \$10 billion loss.

of the losses to put them on a more consistent scale. The charts show that losses by bank and loan category are highly persistent from one year to the next. The correlations in the two charts are 0.96 (left) and 0.97 (right). The correlations are 0.96 and 0.99, respectively, using losses rather than log losses. The loss levels in the Other Loans category are generally small. Including those losses results in a slightly lower correlation. Losses are in billions of dollars, so a $\log_{10}$ value of 1 corresponds to a \$10 billion loss.

Figure 8 pools losses across all banks and categories. To examine individual loan types, we run the following regression for each category c using losses for each bank b:

$$\log_{10}(S_T^{b,c}) = \text{Intercept}_c + \text{Slope}_c \times \log_{10}(S_{T-1}^{b,c}). \tag{3}$$

We run the regressions for $T = 2014$ and $T = 2013$, and we run a pooled regression that combines results for the two years.

Figure 9 summarizes the results. The R^2 is very high in every case except for the Other

Loans category, which may vary widely across banks. The intercepts are close to zero, and the slopes are close to one. The results indicate a high degree of predictability in a bank's projected losses in an individual loan category from one year to the next.

Category	$T = 2014$			$T = 2013$			Pooled		
	Intercept	Slope	R^2	Intercept	Slope	R^2	Intercept	Slope	R^2
First Liens	−0.12**	1.03***	0.93	−0.02	0.98***	0.96	−0.07**	1.01***	0.94
Junior Liens	−0.11**	1.13***	0.94	−0.08	0.84***	0.85	−0.10**	0.97***	0.88
C&I	−0.09**	1.04***	0.95	0.08	0.83***	0.84	0.00	0.92***	0.88
CRE	0.08**	0.93***	0.95	0.12**	1.05***	0.93	0.09***	0.98***	0.93
Credit Cards	−0.02*	0.99***	1.00	0.03	0.96***	0.99	0.01	0.97***	0.99
Other Consumer	−0.03	1.04***	0.97	0.09**	0.89***	0.94	0.03	0.95***	0.94
Other Loans	0.16*	0.92***	0.75	−0.11**	0.89***	0.89	0.02	0.88***	0.75
All Loans (except other)	−0.04***	1.00***	0.95	0.03**	0.91***	0.92	0.00	0.94***	0.92

Figure 9: Regression estimates for log losses on lagged log losses, by loan category, as in (3). The pooled regression combines observations for 2012–13 and 2013–14. "Other loans" are not included in the regressions of All Loans.

Figure 10 compares projected losses in consecutive years in the trading and counterparty loss category. Only six BHCs (JPMorgan Chase, Citigroup, Bank of America, Wells Fargo, Goldman Sachs, and Morgan Stanley) have been subject to this part of the stress test throughout 2012–14, so the comparison is limited to this group. The charts show a high correlation in projected losses from one year to the next. This is more surprising than the corresponding results for the loan categories because trading portfolios change much more quickly than loan portfolios, and trading losses should be more difficult to forecast than loan losses.

The slopes in the two charts are similar, but the intercept adds about $2 billion in losses per bank in 2014. This would appear to reflect the substantial changes made to the shock scenario for trading and counterparty losses from Board of Governors [5] to Board of Governors [6].

Figure 11 summarizes projected stress loan losses over the 2009 SCAP, the 2012 CCAR, and DFAST 2013 and 2014 for the 18 BHCs that participated in all four rounds of stress tests. The chart shows a striking convergence in the projected loss levels for the four largest banks. The average over the other banks in the group of 18 remains stable over time. The chart shows loan losses only and does not include trading and counterparty losses.

Predictability in Loss Rates

The projected loss rate for a given bank in a given category is the corresponding projected loss level divided by the pre-stress value of the bank's assets in that category. Loss rates are more sensitive to small changes than are loss levels, particularly when the denominator is small. For example, Goldman Sachs's C&I loss rate in DFAST 2013 is huge at 49.8 percent. But its

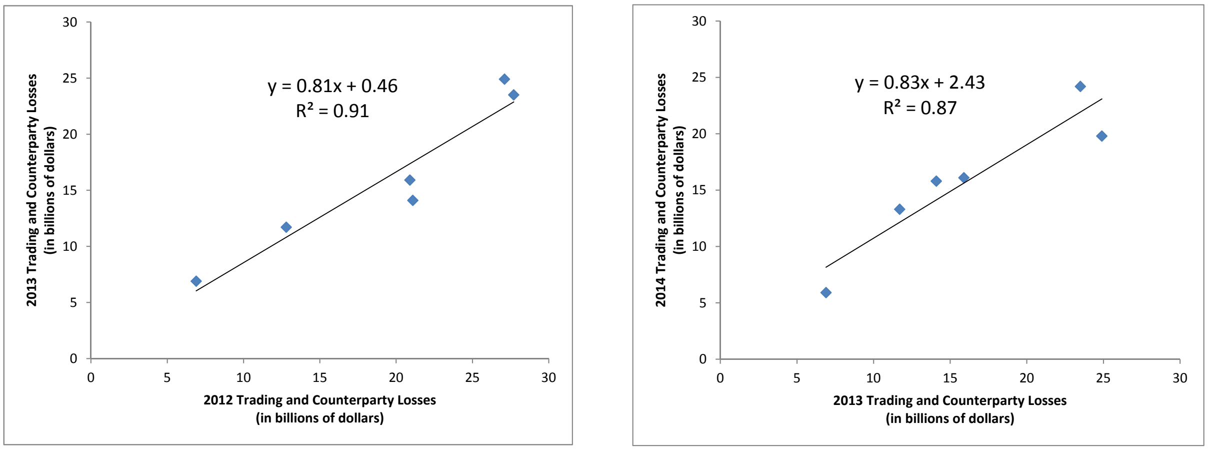


Figure 10: The charts show projected trading and counterparty losses in consecutive years. Each point records values for one BHC. The left chart plots results for DFAST 2013 against CCAR 2012, and the right charge plots DFAST 2014 against DFAST 2013. Losses are in billions of dollars.

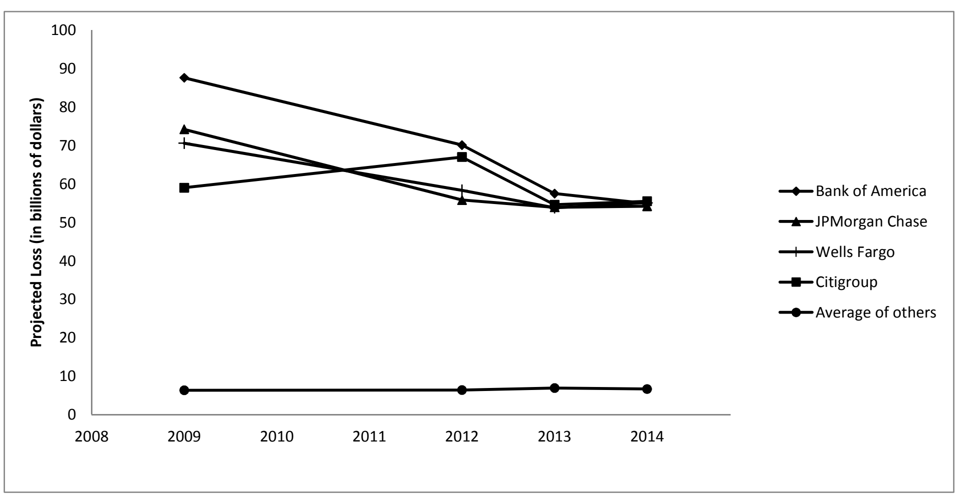


Figure 11: Projected stress loan losses across the 2009 SCAP, the 2012 CCAR, and DFAST 2013 and 2014. The average is taken over the 14 BHCs that participated in all four stress tests and are not shown separately in the chart. The chart shows loan losses only and does not include trading and counterparty losses.

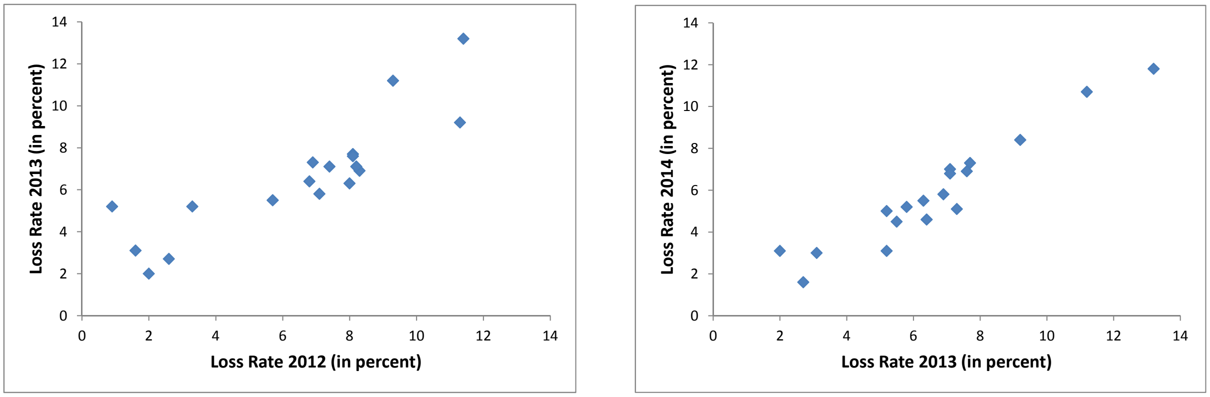


Figure 12: The charts show projected overall loss rates in consecutive years. Each point records values for one BHC. The left chart plots results for DFAST 2013 against CCAR 2012, and the right charge plots DFAST 2014 against DFAST 2013. The correlation is high in both cases and larger for the 2013–14 comparison.

projected loss in that category is only $1.4 billion, below the median projected C&I loss that year and much smaller than Goldman Sachs's projected trading and counterparty loss of $24.9 billion.

Figure 12 compares projected overall loss rates in consecutive years for the 18 BHCs that participated in all three rounds of stress testing. The correlation is high in both cases and larger for the 2013–14 comparison. Each BHC's overall loss rate is the size-weighted average of its loss rates across the seven loan categories. These overall rates are included in the Federal Reserve's CCAR and DFAST reports.

Figure 13 adds detail to this comparison, showing the correlation in loss rates across consecutive years broken down by loan category. In all cases, the 2013–14 correlations are higher than the 2012–13 correlations, suggesting increasing predictability over time.[3]

The correlations vary widely across categories, which makes the predictability of the overall rates in Figure 12 even more surprising. The pattern suggests that banks' overall loss rates are much more stable than their loss rates in individual categories; higher loss rate projections for a bank in one category tend to be offset by lower projections in another category.

The All Loans row in Figure 13 reports the correlation when loss rates for all categories and all BHCs are pooled. The All Loans* row reports the same correlations with the 2013 Goldman

[3]DFAST 2013 and 2014 also disclosed stress projections for pre-provision net revenue (PPNR) and pre-tax net income (PTNI), but earlier reports did not. The correlation between the two years is 0.95 for PPNR and 0.96 for PTNI, measured in dollars. When PPNR and PTNI are measured as a percent of average assets, the correlations fall to 0.88 and 0.72, mostly as a result of the values for Ally. PPNR projections use different models than loan losses; both are inputs to PTNI.

Sachs C&I outlier removed.

Category	2012–13	2013–14
First Liens	0.53	0.70
Junior Liens	0.10	0.41
C &I	0.37	0.46
CRE	0.80	0.88
Credit Cards	0.66	0.98
Other Consumer	0.80	0.99
Other	0.17	0.55
All Loans	0.58	0.74
All Loans*	0.84	0.90

Figure 13: Correlations in loss rates for consecutive years by loan category. The All Loans row pools all loans across all BHCs. All Loans* excludes the 2013 Goldman Sachs loss rate for C&I loans.

We have experimented with using other variables to forecast loss rates, including actual charge-offs reported by the BHCs, stock returns and stock return volatility for individual BHCs. In some cases, actual charge-offs appear to have some forecasting power: BHCs reporting higher loan losses in the prior year often experience higher loss rate projections in the subsequent stress test. However, none of the variables we tested adds much in forecasting stress loss rates compared with using a bank's prior year's stress loss rate.

Stock Market Reaction to Stress Test Results

In this section, we examine the stock market's response to the Federal Reserve's announcement of the 2014 DFAST results. The stock market's response is a measure of the informativeness of the results. We carry out this analysis for the banks that participated in consecutive rounds of stress tests, except that we exclude Ally, which was not publically traded until April 2014.

Peristiani, Morgan, and Savino [16] analyze the market's response to the SCAP, the first of the Federal Reserve's stress tests. They find that the results of the SCAP were highly informative for the banks that were found to require additional capital but not for the banks that "passed" the stress test. Glasserman and Wang [10] find a significant correlation between the value of the SCAP's government backstop and the market's response to the announcement of the terms of the program.

The DFAST 2014 results were announced at 4 p.m. on March 20, 2014. We evaluate the stock market's response by calculating the return for each bank from its closing price on March 20 to its closing price on March 21. To remove the overall effect of the market on that day, for each bank we run a regression

$$BankReturn_{b,t} = \alpha_b + \beta_b MarketReturn_t,$$

using daily returns for one year prior to March 20, 2014, and using the CRSP value-weighted index for the market return. The unexpected component of the stock market response for each bank is the difference

$$\eta_b = BankReturn_{b,T} - (\alpha_b + \beta_b MarketReturn_T),$$

at T =March 21, 2014.

We compare the unexpected returns η_b with the DFAST 2014 stress test results in two ways. First, we measure the correlation between the unexpected returns and the overall loss rates reported. The correlation is positive but very small at 0.12, and not statistically significant. This is consistent with the view that the loss rates reported did not inform the market.

Next, we form a simple forecast of the stress test results. We regress overall loss rates for DFAST 2013 on loss rates for CCAR 2012 (see the left panel of Figure 12), to estimate a_0 and a_1 in the equation

$$LossRate_{b,2013} = a_0 + a_1 \times LossRate_{b,2012},$$

where b indexes the 18 participating BHCs. We use this equation to forecast 2014 loss rates as

$$\widehat{LossRate}_{b,2014} = a_0 + a_1 \times LossRate_{b,2013}.$$

We take the differences between the actual and predicted 2014 loss rates,

$$\epsilon_b = LossRate_{b,2014} - \widehat{LossRate}_{b,2014},$$

as the unexpected component in the stress test results.

Taking these unexpected loss rates rather than the overall loss rates actually increases the correlation with the unexpected market return to 0.29, but this value is still not statistically significant. The higher correlation is surprising: if the unexpected losses were informative, we would expect them to be negatively correlated with the excess returns. But the market likely forms a better forecast of the overall results using additional current information not captured in our simple forecast.

The Federal Reserve's March 20, 2014 announcement included much more than the stress test results. In particular, the CCAR results were announced at the same time. The biggest surprise at the announcement was that Citigroup had "failed" for shortcomings in its internal processes that were not directly related to its projected stress losses. These other, simultaneous announcements make it difficult to isolate the effect of the stress test results, but there is no indication of a significant market reaction to these results.

Discussion

The results of the Federal Reserve's bank stress tests suggest a trend toward greater predictability. In this final section, we discuss implications and possible responses to this trend. We see two primary options.

One option is to accept greater predictability as a consequence of the maturing of the stress testing process. If bank portfolios change slowly, then their capital levels should arguably change slowly as well. And a predictable process still has value: the stress tests require banks to invest in resources for thorough risk assessment with overall benefits for financial stability. The CCAR process includes much more than stress testing, and the other dimensions of the CCAR review may take on greater relative importance than the stress test over time.

The main concern with a routinized stress test is the danger that it will lead banks to optimize their choices for a particular supervisory hurdle and implicitly create new, harder to detect risks in doing so. This concern applies to any fixed supervisory scheme, including one based on risk-weighted assets. (To counter this effect, Glasserman and Kang [9] propose risk weights that adapt to changes in bank portfolios.) We should not expect stress testing to be immune to this concern once the element of surprise is lost. A further concern is that predictability in stress testing may lead to pressures to weaken the process, given the costs involved in its implementation.

A second option is to resist the trend toward predictability. There are at least three ways this might be done, in increasing order of difficulty. First, the adverse and severely adverse scenarios required by DFAST could be differentiated qualitatively to bring greater diversity to the stress testing process, even without increasing the cost of the process. Second, the overall number of scenarios could be significantly expanded to help plug holes inevitably left by just two or three scenarios. Third and most ambitious, the stress testing process could be expanded, as discussed in Bookstaber et al. [7], to include knock-on and feedback effects between institutions, and interactions between solvency and liquidity, leading to a richer set of outcomes than can be achieved through a fixed set of stress scenarios applied separately to each bank. Such a process, though difficult to implement, would respond to changes in the financial and economic environment and would be less likely to get stuck in a predictable outcome.

Acknowledgments. The authors thank Beverly Hirtle for helpful comments and suggestions.

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