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Primer on the Forward-Looking Analysis of Risk Events (FLARE) Model: A Top-Down Stress Test Model

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Primer on the Forward-Looking Analysis of Risk Events (FLARE) Model: A Top-Down Stress Test Model

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Table of Contents

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Introduction

While Dodd Frank Act Stress Tests (DFAST) and the Comprehensive Capital Analysis and Review (CCAR) exercises are critical policy tools for assessing the health of large banks, the Federal Reserve has worked to build additional tools to assess the resiliency of the banking system as a whole and to address macroprudential goals. The Forward-Looking Analysis of Risk Events (FLARE) model is one such tool. This technical note describes the FLARE model, which is a top-down model that helps assess how well the banking system is positioned to weather exogenous macroeconomic shocks. FLARE estimates banking system capital under varying macroeconomic scenarios, time horizons, and other systemic shocks.

FLARE complements DFAST in at least three ways. First, using publically available DFAST macro scenarios, FLARE forms a benchmark assessment of banking system resiliency, as measured by changes in banking system capital. Second, FLARE is flexible. Its specifications are easily updated to reflect the evolving banking system financial conditions, the length of scenarios can be changed, and alternative data sources can be incorporated. FLARE's modularity also allows satellite models to build in feedback effects and fire sales. Finally, because FLARE primarily uses public data, it can test the financial strength of bank holding companies (BHC) including those not in DFAST.[1]

FLARE can also be adapted to address macroprudential stress testing goals. While the DFAST exercise remains critical to assessing banking system vulnerabilities and individual large bank safety and soundness, many macroprudential policy topics, such as funding shocks and fire sales, are outside of the current structure of the public DFAST process. The public DFAST process focuses on institution-specific resiliency among large banks in response to a severely adverse macro scenario. One of its primary goals is to ensure large banks can continue lending under harsh economic conditions. FLARE can be used to answer questions that may not be addressed by public DFAST scenarios. As an example, FLARE was

[1] The terms banks and BHCs are used interchangeably in this paper. However, all data for FLARE and DFAST are based on the BHC.

recently used to assess the impact of prolonged low interest rates, reduced term spreads, and modest gross domestic product (GDP) growth on banking system performance. The tool also informs judgements of the resiliency of the entire banking system, not just large banks, and can be used to assess the relative severity of different macroeconomic scenarios.

FLARE began following the structure of the Capital and Loss Assessment under Stress Scenarios (CLASS) top-down stress testing model (Hirtle et al. 2016). FLARE uses FR Y-9C data to project BHC earnings, losses, and capital under varying macroeconomic scenarios. Section 1 describes the major model assumptions and the projection procedures. Section 2 details development efforts focused on six enhancements. Section 3 addresses how the underlying structures of DFAST and FLARE differ and how their results compare. Finally, section 4 outlines current plans to enhance FLARE.

Section 1: FLARE Assumptions and BHC Projection Procedures

Top-Down Banking System Assumptions

FLARE's top-down framework applies four primary assumptions to each firm in the banking system: constant asset growth, constant balance sheet composition, convergence toward a long-term dividend payout rate, and a constant tax rate. These system-wide assumptions weaken the reliability of individual BHC results, but allow for parsimonious estimates of banking system results. For example, it is arguably unrealistic to assume constant asset growth and fixed balance sheet composition in times of severe economic stress. While banks will likely react strategically with their balance sheet in a time of stress, there is a macroprudential reason for fixing the growth and composition. This assumption does not allow banks to assume that more-favorable liability mixes will be open to them or to shrink their balance sheets in order to meet regulatory minimums. Such shrinkage curtails credit provision. Hirtle et al. (2016) provide a full discussion of the trade-offs associated with these assumptions. In future improvements to FLARE, we plan to make the balance sheet more dynamic, allowing for shifting composition and endogenous growth.

Macroeconomic Scenario Variables

To account for several theoretical and empirical relationships between the banking system and the macro economy, FLARE uses macroeconomic variables, such as interest rates and GDP growth. All macro variables included in FLARE forecasts are a subset of those used in DFAST. Macroeconomic variables and their transformations used in the FLARE model are listed in Appendix A.

Projection Procedures for BHC Pre-provision Net Revenue, Net Charge-offs, and Capital

The projection process begins with regressions of 25 components of pre-provision net revenue (PPNR), net charge-offs (NCOs) for several loan types, and unrealized securities gains/losses. PPNR components are scaled to asset categories.[2] NCOs and unrealized gains/losses are scaled to loan portfolio and securities balances. Regressions use bank quarterly data and take the general autoregressive (AR (1)) form:

$$\text{ratio}_{t,i} = \alpha + \beta\text{ratio}_{t-1,i} + \delta\text{macro}_t + \zeta X_{t,i} + \varepsilon_{t,i.}$$

The dependent variable ($\text{ratio}_{t,i}$) is a linear function of its lag ($\text{ratio}_{t-1,i}$), sensitivity to a vector of macro variables (macro_t), a vector of bank-specific controls ($X_{t,i}$), and an error term ($\varepsilon_{t,i}$). Ratios are converted to dollar values by multiplying by asset categories (PPNR components), loan portfolio totals (NCOs), and securities balances (available–for-sale (AFS) securities).[3] Bank-specific controls are based primarily on FR Y-9C data. However, such data have limited ability to capture risk taking. As a result, some specifications also include data from the FR Y-14 as discussed in section 2. Bank-specific controls are listed in Appendix B. Each regression is run on the largest 200 BHCs and a 201st BHC that is the sum of all other remaining BHCs in the sample.

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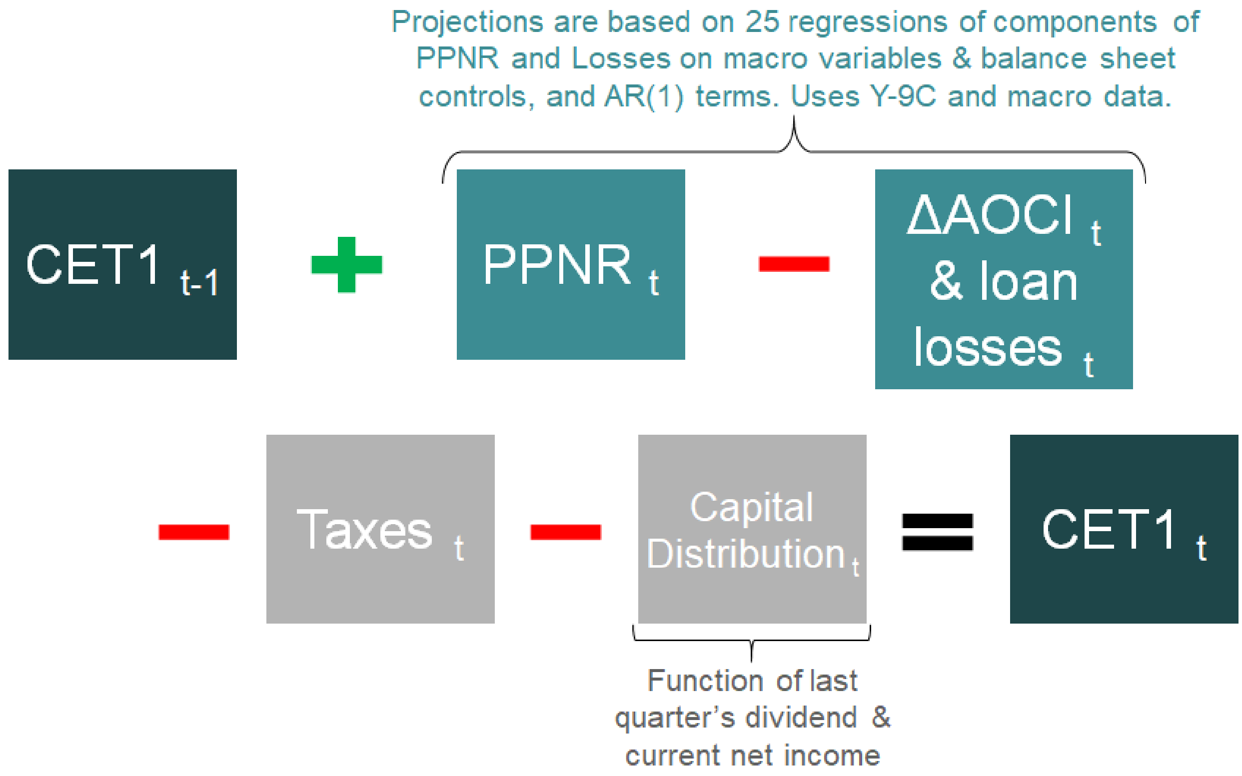
[2] Two components, other noninterest income and other noninterest expense, are not strongly correlated with macro variables. As a result, these two components are projected using the median value for the last eight quarters of data for each bank.

[3] FLARE is consistent with Basel III rules, in which changes in accumulated other comprehensive income (AOCI) from AFS securities become part of the calculation of regulatory capital for category 1 and 2 banks. See https://www.federalreserve.gov/aboutthefed/boardmeetings/files/tailoring-rule-visual-20191010.pdf.

Forecasted losses in FLARE are consistent with supervisory rules and accounting standards that require BHCs to hold reserves to offset probable loan losses in the form of allowances for loan and lease losses (ALLL).[4] Under this guidance, BHCs should hold reserves equal in value to loans that have incurred losses. A rough rule of thumb is that reserves generally cover NCOs over the next one to two years. Because NCOs capture loan losses with a lag, the DFAST framework employs a projection horizon of thirteen quarters in order to construct loan loss provisions for the ninth (final) quarter included in the stress test results. In FLARE, provisions are equal to current quarter NCOs as long as ALLL is within 100 percent to 250 percent of annualized NCOs. If ALLL is too low according to this rule in the final quarter of the forecast period, catch-up provisioning is divided equally across the entire forecast period.[5]

Figure 1: Projection Procedures



[4]ALLL is a function of prior ALLL plus provision expenses for loan and lease losses less NCOs.
[5] This provisioning procedure generally follows a method used in the CLASS model.

Figure 1 shows the sequence of projections in FLARE. The starting point for bank capital forecasts is the prior quarter's capital. Common equity tier 1 (CET1) is the highest quality capital in the regulatory framework and is often the most binding capital constraint for BHCs. As a result, CET1 is the primary measure of capital in FLARE. Next, the coefficients from the regressions, the hypothetical macroeconomic scenarios, and the bank balance sheet data are used to project the 25 components for each BHC that build up PPNR, NCOs, and change in AOCI. NCOs are used to project provisions as described above. Those provisions are subtracted from PPNR to calculate income. Using top-level banking system assumptions, taxes and capital distributions are subtracted from income to forecast retained earnings. Those earnings and change in AOCI are added to the prior period CET1 to generate capital forecasts for each bank.[6] Finally, bank projections are summed to form banking system capital forecasts.

Section 2: Key Differences from Other Top-Down Models

FLARE development efforts have focused on six enhancements:

1. Different merger-adjusted FR Y-9C data,
2. Series smoothing and the treatment of outliers,
3. Refined model specifications,
4. Data from FR Y-14 to capture risk for loan loss estimates,
5. A funding shock overlay, and
6. A scenario library.

Merger-adjusted Data

The Federal Reserve collects consolidated balance sheet and year-to-date income statement data for BHCs using form FR Y-9C. We adjust these data consistent with methods outlined by English and Nelson (1998). First, year-to-date values are converted to quarterly values. Next, we adjust for bank mergers and acquisitions to avoid distortions in quarterly data caused by purchase accounting rules that effectively erase earnings and expenses of the acquired firm. The merger adjustment adds flows from the

[6] FLARE also includes minor adjustments for items such as deferred tax assets and minority interest.

target bank to those of the acquirer by using the target's financials from earlier in the year. These merger-adjusted Y-9C data are the core of the FLARE model.

Treatment of Outliers and Series Smoothing

All dependent variables except NCOs go through a winsorization process in order to avoid outliers that could detract from model performance. Winsorization is generally at the bank level at 3 standard deviations away from the mean of the series. However, because of its AR(1) structure, the observations near the end of the sample period have persistent effects on the trajectory of PPNR and NCO variables. For this reason, these observations warrant special attention. To correct for potential noise and measurement outliers, these observations are winsorized if they fall outside of an even narrower band, usually 2.5 standard deviations away from the mean of the series.

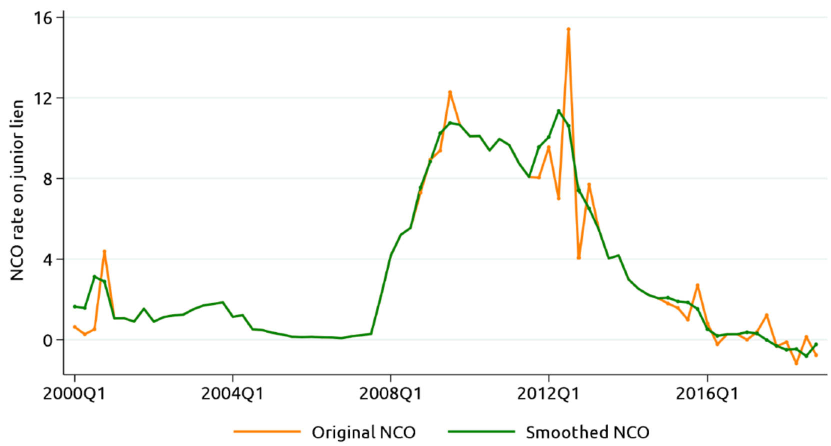
NCOs are adjusted for extreme values in a separate process. First, we adjust NCOs by a simple rule of not allowing them to be lower than 0 percent or larger than 100 percent. Because of factors such as earnings management and allowable differences in loss recognition practices under accounting guidelines, NCOs often display large, abrupt shifts in values that have real economic meaning.[7] This poses an econometric challenge, as large changes are difficult to align with smoother macro series such as the unemployment rate. To help address this, we apply a smoothing technique. We use the NCO numerator, the total dollar amount of non-recoverable debt, to remove spikes in the data. First, quarters of high recognized dollar losses are identified. While keeping the total dollar amount of losses constant, a portion of the losses are then shifted into the three prior quarters. This is done using a smoothing function available in Stata.[8] Finally, NCO rates are recalculated as a percent of each loan portfolio balance. Keeping the total losses constant is important for the analysis. Given that NCOs are already a lagged

[7]For example, Liu and Ryan (2006) provide a discussion of bank earnings management practices through the business cycle.

[8] More specifically, we use smoother(3H) that is a median smoother of span-3 followed by a Hanning smoother. Quarters t and t-1 each receive a weight of one-third. Quarters t-2 and t-3 each receive a weight of one-sixth. See https://www.stata.com/manuals//rsmooth.pdf for more information.

indicator of losses, FLARE is optimizing the capture of all losses. The specific quarter of a loss is less important. Figure 2 shows the smoothing effect for one bank's junior lien mortgages.

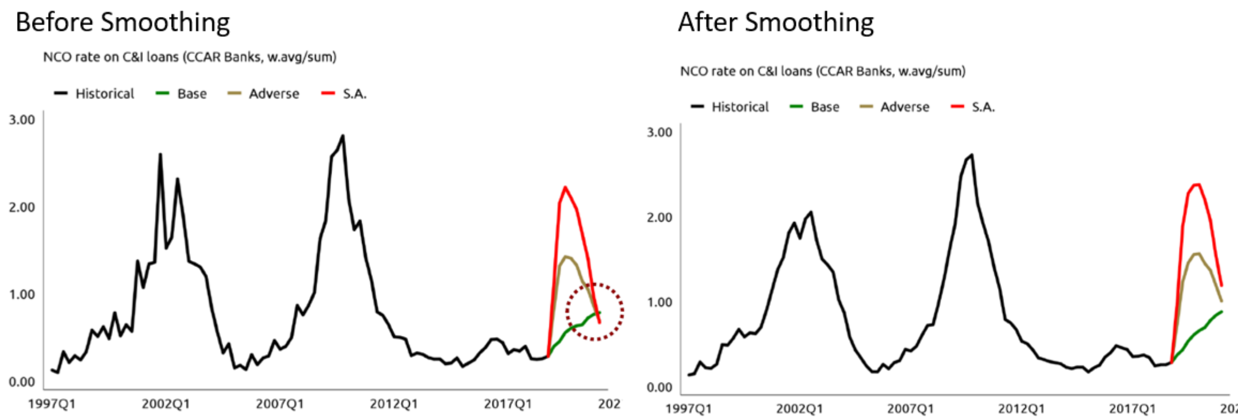
Figure 2: Example of A Bank's Net Charge-off Rate on Junior Lien Mortgages



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies.

Figure 3 shows how DFAST 2019 baseline, adverse, and severely adverse scenarios affect NCOs before and after smoothing the series. Smoothing NCOs in this fashion reduces traditional measures of forecasting errors not only for in-sample results but also, more importantly, for out-of-sample results. As shown below, smoothed NCOs in the severely adverse scenario remain elevated for longer and do not reach the same trough as NCOs in the baseline scenario. This is consistent with a gradual bank balance sheet recovery.

Figure 3: Smoothing Net Charge-offs for DFAST Banks



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; DFAST scenarios.

Changes to Model Specifications

Since the beginning design, FLARE specifications have been enhanced in at least three ways. First, some components of PPNR are segmented and forecasted individually rather than being forecasted as a single dependent variable. Second, NCO regressions are run using panel data rather than industry aggregate data. Lastly, FLARE includes a funding shock overlay that captures the effects of increased interest expenses for firms heavily reliant on short-term wholesale funding.

<u>Pre-provision Net Revenue</u>

Appendix C provides a comparison of dependent variable forecasts for PPNR in FLARE and in CLASS. Notably, FLARE projects interest income and interest expenses as separate dependent variables. Additionally, FLARE projects five noninterest income variables: investment banking and brokerage, fee income, credit card net noninterest income, trading margin, and other noninterest income. We detail credit card net noninterest income in the next section. Compensation agreements at large banks (defined as category 1 and 2 banks) vary significantly from other banks. FLARE accounts for this by separately estimating compensation expenses for both bank types.[9] Similarly, FLARE separates large banks and small banks for trading revenue.

Decomposing Other Accounts: Credit Card Noninterest Income

Other noninterest income and expenses are significant line items. As an example, in 2018, other noninterest income accounted for about 25 percent of total noninterest income, while other noninterest expenses accounted for about 40 percent of total noninterest expenses. These summary accounts contain miscellaneous sources of revenue and expenses, such as credit card fees and litigation expenses that are not captured by the other PPNR components. Because these line items contain a host of uncorrelated activities, the aggregates lack a robust relationship with macroeconomic series.

More recently, certain accounts have been established to track the credit card fees in FR Y-9C. In particular, the interchange fee series and expense series were first available during the first quarter of 2008. Building on the approach of Kovner et al. (2014), we use Y-9C memoranda text fields to historically reconstruct a series for credit card net noninterest income (CCNII) which is equal to interchange fees and annual fees less card rewards. Text fields from the Y-9C are available from 1997 forward. Text fields are non-standardized items that banks self-report if they are least $100,000 and 7 percent of other noninterest income or noninterest expense. Because we do not consistently observe CCNII, only its boundaries, we use an interval regression, dependent on the change in the unemployment rate, to estimate CCNII. This constructed component is very useful for projecting PPNR as it is equivalent to 40 percent of other noninterest income on average, and provides important information about bank-specific variation given the high concentration of credit card loans.

Net Charge-offs and Credit Risk Dimensions

While FR Y-9C is useful for evaluating long-term trends in banking system balance sheets and income statements, it lacks detailed measures of credit risk and underwriting quality such as credit scores

[9] Category 1 banks include the eight U.S. global systemically important banks. Category 2 banks have total assets greater than or equal to $700 billion or cross-jurisdictional activity greater than or equal to $75 billion.

or probability of default. Three of the NCO regressions have been enhanced to include data from FR Y-14 and Call Reports (FFIEC 031/041): credit cards, other consumer, and commercial and industrial (C&I) loans. Incorporating the share of subprime credit card loans and high loan-to-value auto loans from the Y-14 help refine NCO projections for credit cards and other consumer loans. Including C&I yields from Call Reports add predictive power to C&I NCO estimates. One cost of this choice is a restricted sample period. FR Y-14 portfolio data begins as early as 2007:Q1 and only covers DFAST BHCs. In contrast, FR Y-9C variables are generally available beginning 1997:Q1 and cover all BHCs modeled by FLARE. The Call Report data for the commercial bank subsidiaries of a BHC contains more-granular information on certain assets and liabilities. Thus, by aggregating across all banks in the same holding company, we can use the Call Report to supplement the Y-9C. This was useful for C&I yield estimates, because the Call Report data has more information on sources of interest income. However, the data does not capture business lending if it is done in a BHC's nonbank subsidiaries. Dependent net charge-off variables are shown in Appendix D.

Funding Shock Overlay

There are several financial spillovers that are important for macroprudential policy but are not currently included as part of DFAST. As an example, during a funding shock, banks heavily reliant on short-term wholesale funding (STWF) may experience significant increases in funding costs.[10] FLARE includes an optional funding shock overlay, which projects interest expense increases associated with changing STWF spreads as a function of bank solvency (CET1 ratios) and wholesale funding industry interest rate data.[11] This is an optional overlay to allow for stress testing with and without a wholesale funding shock.

[10] STWF is defined as federal funds, repurchases, commercial paper, and foreign interest bearing deposits. Large time deposits, brokered deposits, and other interest borrowings with less than 1-year maturity are also included.
[11] This is modeled using the methodology of Bassett and Rappoport (2020).

Dynamic Scenario Library

FLARE is designed to assess banking system performance under a variety of macroeconomic scenarios. A scenario library was created to form a distribution of potential macroeconomic shocks to the banking system. The library draws on stress scenarios created by both policy makers and BHCs.

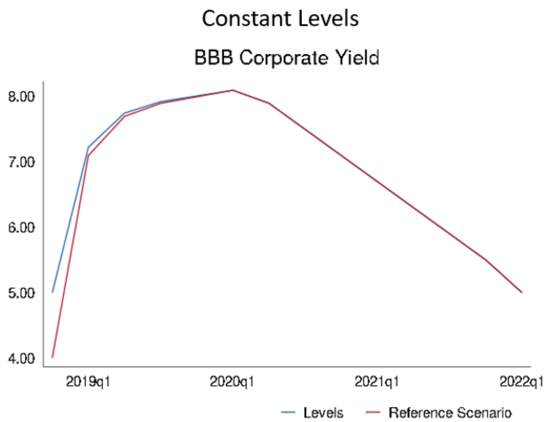
As part of the annual DFAST process, each BHC submits a severely adverse stress scenario that is tailored to its specific business model and portfolio vulnerabilities.[12] These are denoted as BHC severely adverse scenarios. The scenario library contains BHC severely adverse scenarios from 2014 to 2019 for all CCAR banks. Additionally, supervisory adverse and supervisory severely adverse scenarios, which are created by Board staff and published in DFAST results, are included in the scenario library. These scenarios can be assessed using bank balance sheets and macro conditions at the time when the scenarios were created or in present terms, using the most recent bank balance sheet and macro data available.

A challenge arises when scenarios are applied to a jump-off point at a different date with different macroeconomic conditions. The jump-off point can differ significantly from when a scenario was first designed. As an example, if policy makers want to gauge the severity of macro scenarios from 2017 in today's environment, each variable must start from the most recent quarterly observation. There is a variety of methods to shift a macro series through time. We highlight three methods used in FLARE:

1. Levels: make the updated scenario achieve the *level* (peak or trough) observed in the original reference scenario and in the same forecast quarter,
2. Changes: mimic the path of *changes* observed in the original reference scenario, and
3. Shift: shift all values in the macro variable path up or down to match the new jump-off point.

[12] See, for example, the instructions from the 2019 exercise here (page 8) https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20190306b2.pdf.

Figure 4: Scenario Variables in Levels and Changes



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; DFAST scenarios.

Figure 4 provides examples of the levels approach and changes approach. On the left, the BBB yield in present terms (shown in blue) achieves the same level as the BBB yield from the original reference scenario (shown in red). On the right, the changes in the stock market (shown in blue) mirror the path of changes in the stock market from the original reference scenario (shown in red).

Financial variables that experience large relative declines in times of economic stress, such as the stock market and real estate prices, are typically transformed using the changes approach. Macro variables that have a tendency to converge toward specific maximum or minimum value under stress, such as unemployment, are typically updated using the levels approach. Adjustments can be made to the scenario in the event that the relationships observed between updated variables are inconsistent with economic theory or convey inappropriate levels of stress. The type of transformation selected is also based on the general behavior of a variable and how the variable is used in the model. For example, GDP growth enters FLARE components without further transformations. In addition, GDP growth captures a dimension of scenario severity. Therefore, GDP growth is generally not changed when shifting a scenario through time.

With a macro-enhanced spreadsheet, custom macro scenarios can also be generated and loaded into the FLARE model with ease. Overall, the scenario library enhancement helps evaluate shocks viewed as likely from the perspective of the banking industry, as well as evolving risks as seen by policy makers.

Section 3: How Do DFAST and FLARE Results Compare?

The public DFAST exercise is designed to test whether each large bank is capable of maintaining its financial strength in order to support its core intermediation functions under severe macroeconomic conditions. As such, DFAST models rely on granular, confidential data to fit the custom risk profile of each bank to project PPNR as well as market and loan losses. By contrast, FLARE relies on mostly public data and is designed to evaluate vulnerabilities for broader categories of banks within the banking system, with less emphasis on risks of individual banks. It does not include the global market shock or operational risk as included in the DFAST exercise. While estimates from FLARE are parsimonious, they are consistent with DFAST and provide intuitive results. This section provides comparisons of DFAST and FLARE results.

We start with a comparison of FLARE and DFAST results from 2017 to 2019. To make these comparisons, FLARE creates estimates only for those banks subject to stress testing under DFA. The comparisons focus on results using the supervisory severely adverse scenario over the nine-quarter projection horizon. As shown in table 1, over the past three DFAST cycles, FLARE has produced consistently lower projections of PPNR and NCOs as a percent of risk-weighted assets. The NCO bias is consistent with FLARE having less sensitive measures of loan risk. On net, FLARE projections of the difference between PPNR and NCOs, depicted in the last two columns, fall within 30 basis points of DFAST model projections.

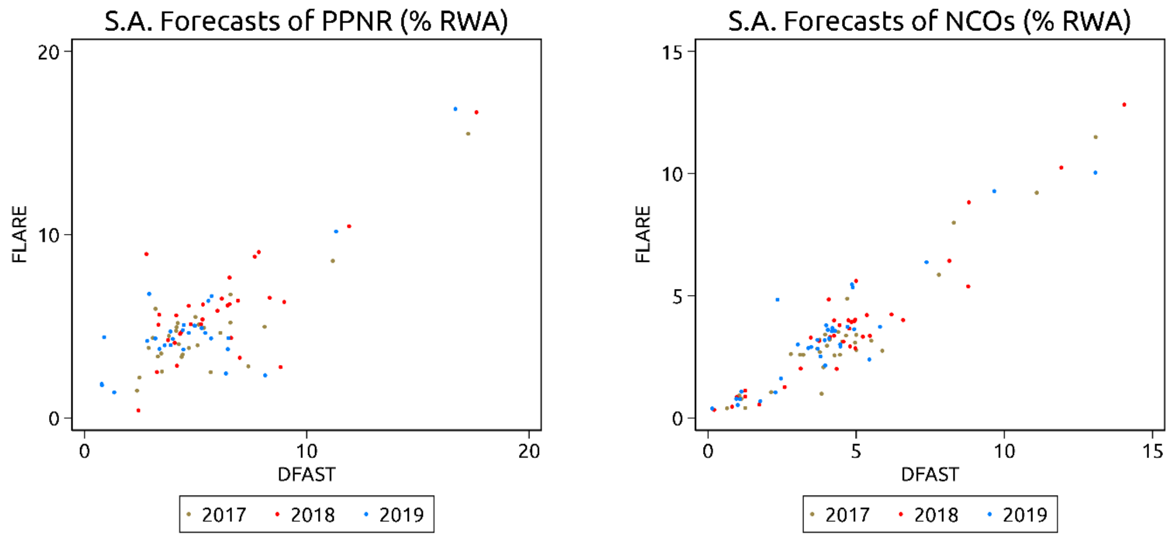
Table 1: Aggregate Comparison of FLARE and DFAST Results for DFAST Banks by Year

[% of RWA]	PPNR		NCOs		PPNR - NCOs	
Year	FLARE	DFAST	FLARE	DFAST	FLARE	DFAST
2017	4.3	5.5	3.0	3.9	1.3	1.6
2018	5.3	6.3	3.5	4.3	1.8	2.0
2019	4.4	5.4	3.3	4.0	1.1	1.4
Average	**4.7**	**5.7**	**3.3**	**4.1**	**1.4**	**1.7**

Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; DFAST scenarios and results; FLARE calculations.

Because FLARE is a top-down model and lacks dimensions of portfolio and operational risks unique to each institution, its results will not reflect BHC-specific risks with the same sensitivity as DFAST. DFAST models do not use NCOs but more granular data that capture expected losses based on probability of default, loss given default, and exposure at default. Thus, comparisons of BHC results between DFAST and FLARE should be interpreted with caution. Despite these limitations, FLARE results are correlated with DFAST results at the firm level. Figure 5 highlights PPNR and NCO firm-level results from DFAST severely adverse scenarios from 2017 to 2019. If FLARE and DFAST had the same prediction, each bank, represented separately by a dot, would fall along the 45-degree line. The dots generally cluster around that line.

Figure 5: Comparison of FLARE and DFAST Results for DFAST Banks by Year



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; DFAST scenarios and results; FLARE calculations.

Section 4: Future Plans for FLARE

FLARE model development will likely focus on two types of improvements in the short-term. First, there are several loan portfolios estimated in FLARE that could be improved by including data on risk taking available through FR Y-14 and other sources. Similar to the refinements implemented for credit card NCOs, our first priority is to focus on incorporating risk measures that add to the macro sensitivity of the model and inform loss estimates. Second, to bring more depth to FLARE as a macroprudential tool, the balance sheet needs to be more dynamic. As part of that, the current funding shock overlay can be improved and longer scenarios can be considered to incorporate a prolonged period of very low interest rates or a "double-dip" recession. In addition, future versions of FLARE should estimate how fire sales may pose a risk to banking system resiliency.

References

Bassett, William F. and David E. Rappoport W. (2020) “Enhancing Stress Tests by Adding Macroprudential Elements.” In: *Handbook of Financial Stress Testing*, edited by J. D. Farmer, A. Kleinnijenhuis, T. Schuermann, and T. Wetzer. Cambridge University Press, forthcoming.

English, William B., and William R. Nelson (1998) "Profits and Balance Sheet Developments at U.S. Commercial Banks in 1997," *Federal Reserve Bulletin*, vol. 84, no. 6, pp. 391-419

Hirtle, Beverly, Anna Kovner, James Vickery, and Meru Bhanot (2016) “Assessing Financial Stability: The Capital and Loss Assessment under Stress Scenarios (CLASS) Model.” *Journal of Banking & Finance* 69, pp S35-S55.

Kovner, Anna, James Vickery, and Lily Zhou (2014) “Do Big Banks Have Lower Operating Costs?” *Economic Policy Review*, Federal Reserve Bank of New York, 20(2), March.

Liu, Chi-Chun, and Stephen G. Ryan. (2006) “Income Smoothing over the Business Cycle: Changes in Banks' Coordinated Management of Provisions for Loan Losses and Loan Charge-Offs from the Pre-1990 Bust to the 1990s Boom.” *The Accounting Review*, vol. 81, no. 2, pp. 421–441.

Appendix A: Macroeconomic Scenario Variables

Variable	Transformation(s)
3-month Treasury yield*	Level
5-year Treasury yield*	Level
10-year Treasury yield*	Level
	Annualized rate of change
Term spread (10-yr Treasury – 3-mo. Treasury)	Level
	Annualized rate of change
	Quarterly change; if spread <0, replace with zero
BBB corporate yield*	Level
BBB corporate bond spread (BBB - 10-yr Treasury)	Level
	Annualized rate of change
	Quarterly change; if spread <0, replace with zero
Mortgage rate*	Level
Prime rate*	Level
CBOE volatility index (VIX)*	Level
	Log
CoreLogic U.S. house price index*	Level
	Log 8 quarter change
	Lagged quarterly log change
	Quarterly change; if spread >0, replace with zero
CPI inflation rate*	Annualized rate of change
CRE price index*	Level
	Quarterly change; if spread >0, replace with zero
	Log quarterly change
DJ U.S. total stock market index*	Level
	Log quarterly change
Real disposable income*	Annualized rate of change
Real GDP*	Annualized rate of change
Unemployment rate*	Level
	Annualized rate of change

* Consistent with methodology disclosed in Supervisory Scenarios for Annual Stress Tests Required under the Dodd-Frank Act Stress Testing Rules and the Capital Plan Rule

For 2019 DFAST disclosure details, reference
https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20190213a1.pdf

Appendix B: Bank-specific Controls

Variable
Loan composition (percent of interest-earning assets)
Residential real estate
Commercial real estate
Commercial and industrial
Consumer credit card
Other consumer
Funding (percent of interest-earning assets)
Non-time deposits
Short-term funding
Long-term funding
Other
All other (percent of interest-earning assets)
Trading assets
Securities
Market share of total assets
All other (percent of assets)
Investment banking and brokerage income
Fair value of available-for-sale (AFS) assets
Credit quality
Credit card subprime share
Auto loan-to-value share
Commercial and industrial loan yield

Appendix C: Comparison of PPNR Dependent Variables

	FLARE	CLASS
Income		
Interest income		
Net interest margin		x
Interest income	x	
Interest expense	x	
Noninterest income		
Noninterest nontrading income		x
Investment banking and brokerage	x	
Fee income	x	
Credit card noninterest income	x	
Return on trading assets		x
Trading margin for trading banks	x	
Trading margin for non-trading banks	x	
Noninterest expenses		
Compensation expenses		
Compensation noninterest expense		x
Compensation noninterest expense category 1 and 2 banks	x	
Compensation noninterest expense all other banks	x	
Fixed asset noninterest expense ratio	x	x
Other noninterest expense ratio	x	x

Appendix D: Net Charge-Off Dependent Variables

Variable
Real estate net charge-offs
First lien residential real estate
Junior lien residential real estate
Home equity
Construction
Multifamily
Nonfarm nonresidential
Other consumer
All other net charge-offs
Credit card
Commercial and industrial
Leases
Other real estate
Foreign government
Agriculture
Other