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

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Introduction

While the bank stress test exercise conducted by the Federal Reserve System is a critical policy tool 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 the annual stress test exercises in at least three ways. First, by using the same publicly available macro scenarios from the larger exercise, 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 the official stress tests.[1]

FLARE can also be adapted to address macroprudential stress testing goals. While the official 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 official exercise. The official exercise 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 the official scenarios. As an example, FLARE has been used to

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

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 by following the structure of the Capital and Loss Assessment under Stress Scenarios (CLASS) top-down stress testing model (Hirtle et al. 2016). As such, 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 other data refinements. Section 3 describes development efforts focused on seven enhancements. Finally, section 4 outlines current plans to enhance FLARE.

Section 1: FLARE Assumptions and BHC Projection Procedures

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 the official stress test exercise. Macroeconomic variables and the transformations used in the FLARE model are listed in Appendix A.

Top-Down Banking System Assumptions

FLARE's original top-down framework applied 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. Recent improvements to FLARE allow the option for more dynamic responses from banks and are discussed next.

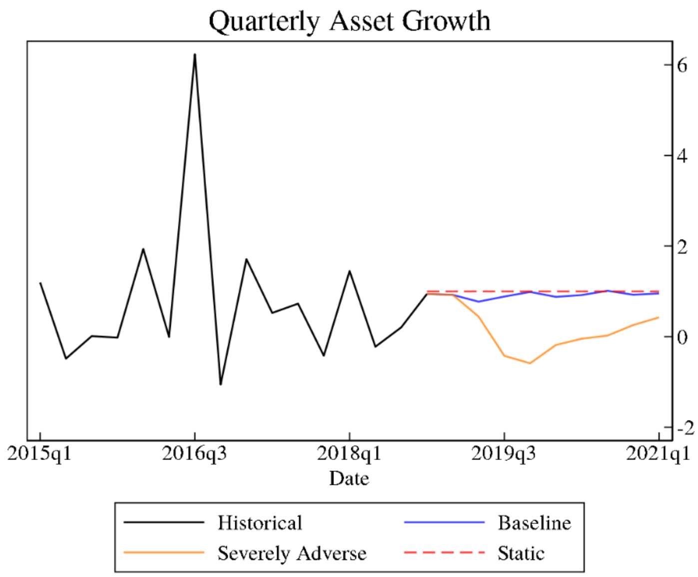
Endogenizing Banking System Asset Growth and Balance Sheet Composition

To implement a more dynamic balance sheet, we start by estimating growth in aggregate banking system assets using a vector autoregression model (VAR). The VAR models how the log level of assets fluctuates with macroeconomic and financial conditions. The VAR uses quarterly, seasonally adjusted total assets from the H.8 data release.[2] We test a variety of specifications using public macro and financial variables from the official stress test exercise. Our primary VAR specification, which was selected based on Akaike information criterion optimal lag lengths as well as out-of-sample performance, includes the lags of the log level of assets, log GDP, and the unemployment rate. This allows us to project a quarterly growth rate of banking system assets throughout the projection horizon, which we apply uniformly to all banks in our sample.

Figure 1 shows projected asset growth using a VAR levels specification for three scenarios: a static growth assumption and two scenarios from the 2018 stress testing exercise (baseline and severely adverse). In prior versions of the model, assets grew at a static rate of one percent per quarter (red line) which closely aligns with VAR asset growth projections in the baseline (purple). In the severely adverse scenario, asset growth tends to decline as the economic conditions deteriorate and tends to increase as conditions improve (orange line).

[2] This data set is used because it has a much longer time series to capture business cycle dynamics. More information on the series is available on the Federal Reserve Board website https://www.federalreserve.gov/releases/h8/current/default.htm.

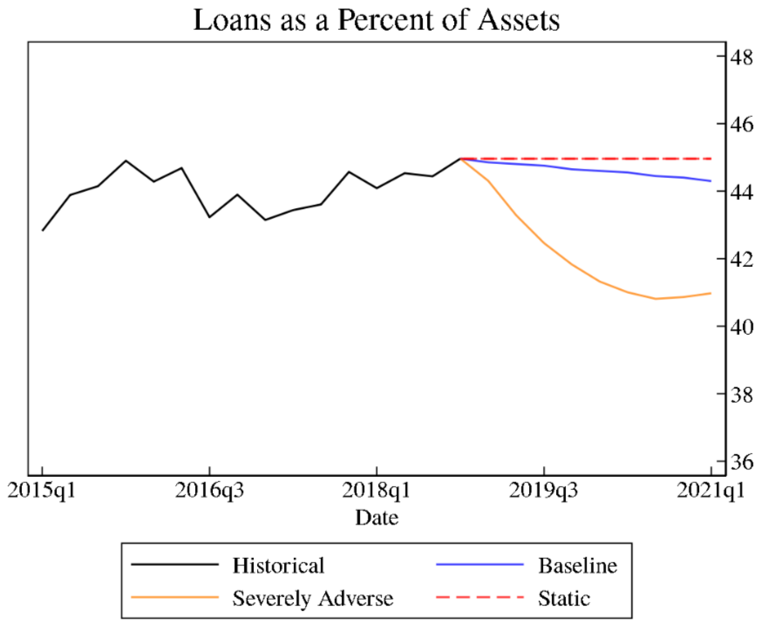
Figure 1: Asset Growth by 2018 Scenarios



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

In addition to asset growth, FLARE now also allows for flexible asset composition. More specifically, we model loans as a share of assets using the panel dataset. We focus on loan shares as they compose about half of large banks' assets. Similar to the pre-provision new revenue (PPNR) component models, we estimate loan shares using an autoregressive term and macro variables. Bank loan shares evolve slowly in baseline conditions and tend to decline under stress in the model, consistent with prior business cycle dynamics. Figure 2 shows the path of loan shares in the baseline and severely adverse scenarios, compared to the static case. We project non-loan assets, such as cash and Treasury securities, as the residual with respect to loan shares (i.e., "1 – loan shares").

Figure 2: Loan Share by 2018 Scenarios



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

Because balance sheet composition characteristics enter PPNR and loan loss regression specifications, changes in balance sheet composition require iterative forecasting—forecast one quarter at a time. The forecasting process is sequenced as follows:

- Run regressions for model components: PPNR, loan losses, and accumulated other comprehensive income (AOCI)
  - This establishes the beta loadings for component forecasts
- Calculate asset growth based on VAR results
- Forecast bank-level loan shares and non-loan shares
- Quarter by quarter procedure
  - Project model components
  - Calculate capital

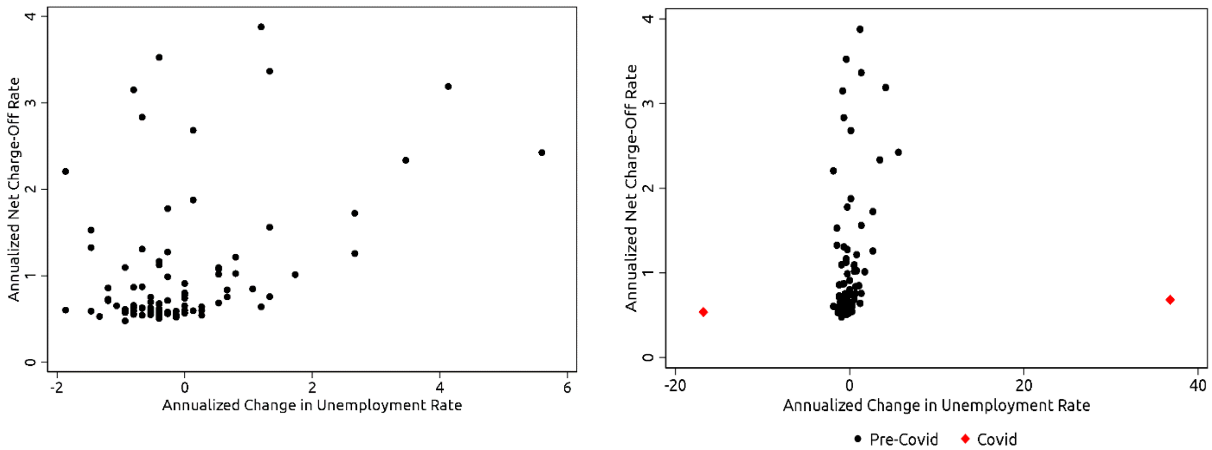
As an example of the importance of iterative forecasting, net interest income loads on an autoregressive term, loan shares for many loan types, and other macro and financial variables. By incorporating the updated loan shares in our model, we ensure that net interest income projections are consistent with changes in the asset composition. From figure 2, we would expect a material decrease in net interest income in the severely adverse scenario, given the decline in loans as a fraction of assets.

The change in asset composition also changes risk-weighted assets. We estimate the change in risk-weighted assets associated with the change in the level and composition assets by calculating risk-weights for loans and non-loans for each bank and applying those weights to projected loans and to projected non-loans. respectively.

Model Adjustments Due to the COVID-19 Pandemic

The large and rapid changes in the unemployment rate and relatively low loan charge-offs during the COVID-19 pandemic have challenged our traditional loan loss modeling methods. Figure 3 plots the annualized quarterly change in the national unemployment rate and annualized net charge-offs. Each dot represents a quarter, and net charge-offs are calculated at the aggregate level (across FR Y-9C filers). The left panel uses a sample from 1997:Q1 through 2020:Q1, and the right panel extends the sample through 2020:Q3. To preserve the macro sensitivity of the model, we drop outliers associated with the pandemic before estimating coefficients. Projections still jump-off from current quarter balance sheet data.

Figure 3: Net Charge-offs and Unemployment Rate



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

Projection Procedures for PPNR, Net Charge-offs, and Capital

The projection process begins with regressions of components of PPNR, net charge-offs (NCOs) for several loan types, and unrealized securities gains/losses. PPNR components are scaled to asset categories. NCOs and unrealized gains/losses are scaled to loan portfolio and securities balances, respectively. Most 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 balances (NCOs), or 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 3. Bank-specific controls

[3] FLARE is consistent with Basel III rules, in which changes in 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.

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. 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.

PPNR Components Not Calculated Using Full Panel Regressions

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.[4] Other noninterest income and other noninterest expense are volatile and do not tend to correlate with any of the macro variables in the official stress test scenarios. As a result, both components are projected by simply using each bank's eight-quarter median. Section 3 discusses the projection procedures for trading margin and credit card net noninterest income.

Forecasting Provisions

Forecasted loan losses in FLARE are consistent with the incurred loss method (ILM), 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). Under this guidance, BHCs should hold allowances equal in value to loans that have incurred losses. A rule of thumb is that allowances generally cover NCOs over the next one to two years. In FLARE, provisions are equal to current quarter NCOs plus coverage of near-term losses. Specifically, the remaining ALLL needs to be within 100 to 250 percent of the NCOs projected for the next four quarters. Because modeled NCOs will not match perfectly to ALLL at jump-off, provisions will also need to be adjusted to capture this gap. This true-up is spread evenly over the projection horizon.[5] Also notice that the macro scenario needs to be longer than the stress test

[4] 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.
[5] This provisioning procedure generally follows a method used in the CLASS model.

projection horizon. The official stress test exercise scenarios are published out to thirteen quarters. This allows FLARE to construct loan loss provisions for the ninth (final) quarter.

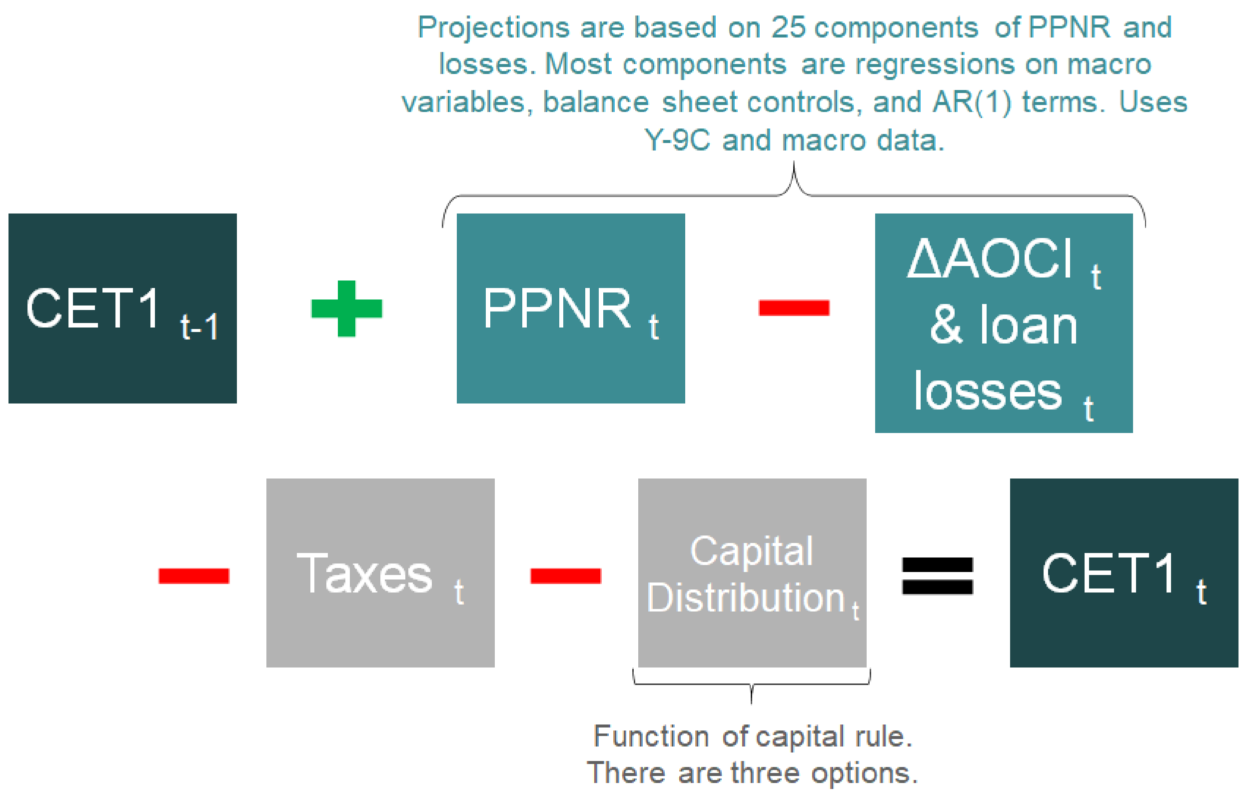
Changing the provision estimation to a quarter-by-quarter projection was important for future work that will implement a recent accounting change. Most large U.S. banks adopted Current Expected Credit Losses (CECL), a new accounting standard for estimating allowances, on January 1, 2020. CECL requires banks to maintain an allowance that covers expected losses over the contractual life of a loan. By contrast, the "loss emergence period" under ILM is typically shorter. As a result, allowances are generally higher under CECL. For future work, there are at least three ways to better-align the treatment of loan loss projections in FLARE with CECL. First, the four-quarter look ahead assumption may need to be extended to reflect the longer time horizon and could vary by loan type. Second, under CECL, banks estimate losses over a reasonable and supportable forecast horizon and can then revert to historical relationships for the balance of the contractual life of the loan. Because forecasts become less reliable at extended horizons, weights may need to be adjusted for longer-term projected loan losses. For example, it may be appropriate to fully weight NCOs occurring during the first year of the projection horizon, while applying discount factors to projected NCOs at more extended horizons. The latter years could also be estimated using historical relationships.

Figure 4 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.[6] 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

[6] The leverage ratio has also been added. This is discussed further in section 3.

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.[7] Finally, bank projections are summed to form banking system capital forecasts.

Figure 4: Projection Procedures



Section 2: Preparation of Data

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

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

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 target bank to those of the acquirer by using the target's financials from earlier in the year. These merger-adjusted FR 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 three 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.[8] 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.[9] Finally, NCO rates are recalculated as a percent of each loan portfolio balance.

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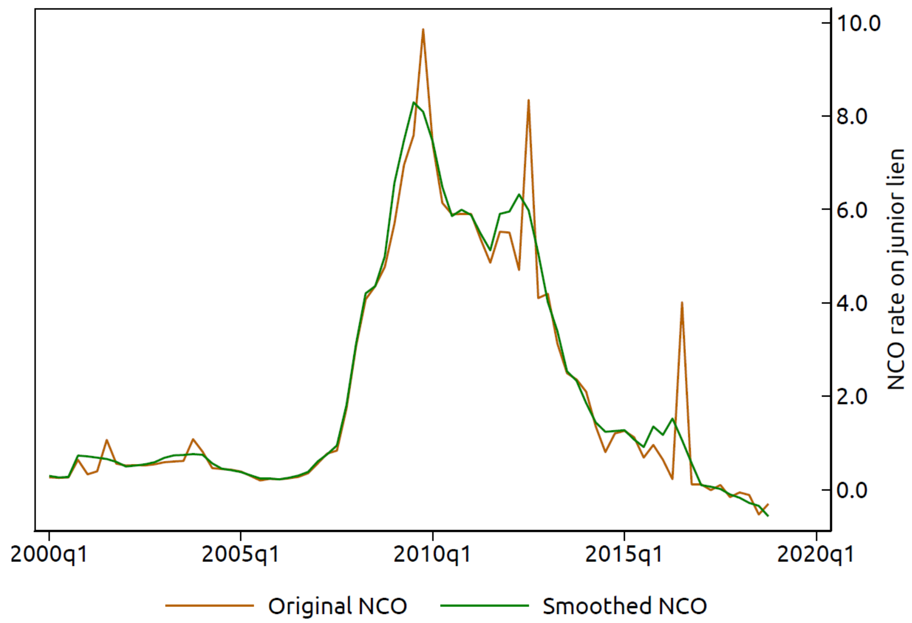
[8]For example, Liu and Ryan (2006) provide a discussion of bank earnings management practices through the business cycle.

[9] 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.

Keeping the total losses constant is important for the analysis. Given that NCOs are already a lagged indicator of losses, FLARE is optimizing the capture of all losses. The specific quarter of a loss is less important. Figure 5 shows the smoothing effect for banking system junior lien mortgages.

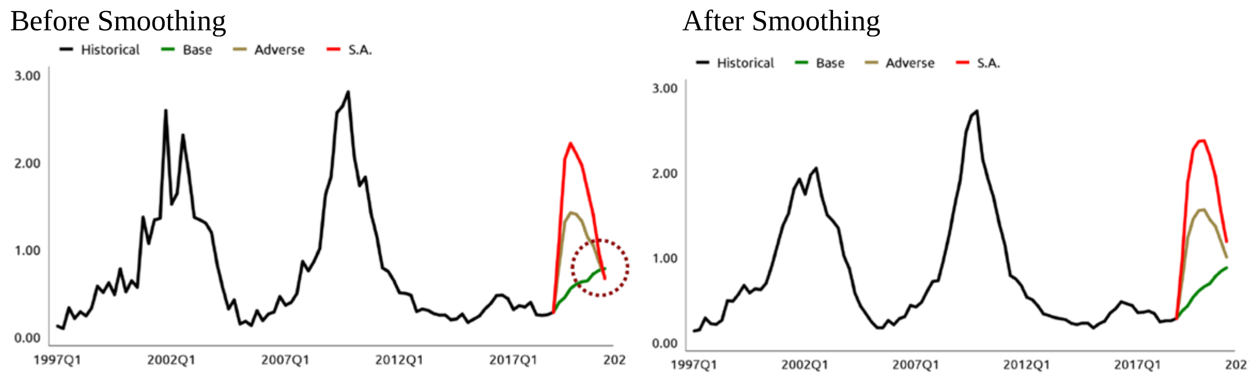
Figure 5: Example of Banking System Net Charge-off Rate on Junior Lien Mortgages



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

Figure 6 shows how baseline, adverse, and severely adverse scenarios from the 2019 official exercise 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 6: Smoothing Net Charge-offs for Business Loans



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

Section 3: Further Innovations

Changes to Model Specifications

Since the beginning design, FLARE specifications have been enhanced in at least two ways. First, some components of PPNR are segmented and forecasted individually rather than being forecasted as a single dependent variable. These were described above. Second, NCO regressions are run using panel data rather than industry aggregate data.

Supplementing Trading Margin Data

Similar to the treatment of compensation expense, FLARE separates large banks and small banks for trading margin. A separate regression is run for two different groups of banks: more active traders and less active. The active group is defined as any bank with trading assets of 5 percent or more of total assets. We also supplemented FR Y-9C data with public Securities and Exchange Commission (SEC) data. More specifically, Goldman Sachs and Morgan Stanley have material trading exposures and were not FR Y-9C filers until 2009. Proxies for trading revenues and trading assets were collected from 10-Q and 10-K filings to extend the time series back to 2000. The additional data improved the out-of-sample performance for trading margin (trading revenue/trading assets) projections.

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 FR 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 FR 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 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 FR 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 BHCs that are stress tested. 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 FR 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.

Additional Options for Capital Distributions

Projected capital distributions followed an AR process in prior versions of FLARE. The model now includes added flexibility to set payouts equal to a firm's prior quarter payouts or to the four-quarter average of payouts.

To preserve capital under stress, banks that breach regulatory capital buffer requirements are subject to capital distribution limitations as a fraction of eligible retained income. Prior versions of the model assumed payouts would continue under stress, regardless of a firm's CET1 capital level relative to its requirements. The current version of FLARE limits capital distributions if a firm breaches its capital requirements, consistent with current rules. Table 1 shows capital distribution rules for non-stress tested banks breaching their capital conservation buffer. Similar rules apply to tested banks, where their buffer is equal to the sum of their firm-specific stress capital buffer and GSIB surcharge.

Table 1: Calculation of Maximum Payout Amount

Capital conservation buffer	Maximum Payout Ratio
Greater than 2.5 percent plus 100 percent of the Board-regulated institution's applicable countercyclical capital buffer amount	No payout ratio limitation applies.
Less than or equal to 2.5 percent plus 100 percent of the Board-regulated institution's applicable countercyclical capital buffer amount, and greater than 1.875 percent plus 75 percent of the Board-regulated institution's applicable countercyclical capital buffer amount	60 percent.
Less than or equal to 1.875 percent plus 75 percent of the Board-regulated institution's applicable countercyclical capital buffer amount, and greater than 1.25 percent plus 50 percent of the Board-regulated institution's applicable countercyclical capital buffer amount	40 percent.
Less than or equal to 1.25 percent plus 50 percent of the Board-regulated institution's applicable countercyclical capital buffer amount and greater than 0.625 percent plus 25 percent of the Board-regulated institution's applicable countercyclical capital buffer amount	20 percent.
Less than or equal to 0.625 percent plus 25 percent of the Board-regulated institution's applicable countercyclical capital buffer amount	0 percent.

Source: https://www.ecfr.gov/current/title-12/chapter-II/subchapter-A/part-217.

FLARE can be used to evaluate banking system resiliency across large and small banks. While large banks are generally constrained by risk-based capital requirements such as the CET1 ratio, smaller banks, such or those with less than $10 billion in consolidated assets, may be constrained by leverage requirements. The current version of FLARE includes the community bank leverage ratio, tier 1 capital divided by total assets. This is an important addition to help evaluate the resiliency of smaller banks. Banks that qualify for the community bank leverage ratio are not required to report risk-weighted assets, the denominator of the CET1 ratio.

Funding Shock Overlay

There are several financial spillovers that are important for macroprudential policy but are not currently included as part of the official stress test exercise. 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.

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 official annual process, each BHC submits an adverse stress scenario that is tailored to its specific business model and portfolio vulnerabilities.[12] These are denoted as BHC adverse scenarios. The scenario library contains BHC adverse scenarios from 2014 to 2021 for all tested banks. Additionally, supervisory adverse and supervisory severely adverse scenarios, which are created by Board staff and published in official 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.

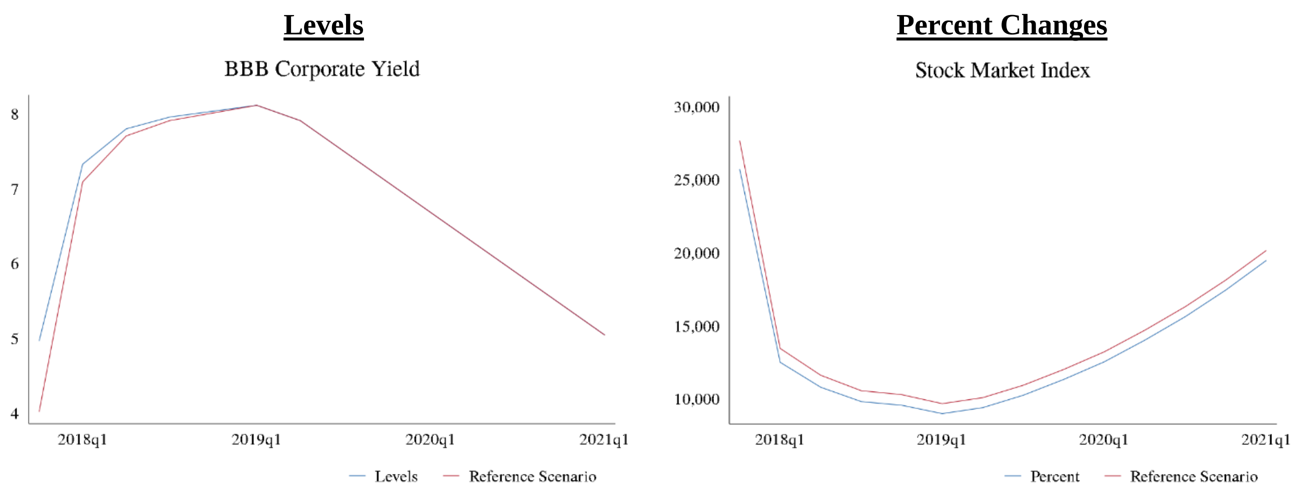
A challenge arises when scenarios are applied to a jump-off point at a different date with different macroeconomic conditions. The jump-off point can differ significantly from when a scenario was first designed. As an example, if policy makers want to gauge the severity of macro scenarios from 2017 in 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,

[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 one-year maturity are also included.
[11] This is modeled using the methodology of Bassett and Rappoport (2020).
[12] See, for example, the instructions from the 2019 exercise here (page 8) https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20190306b2.pdf.

2. Percent changes: mimic the path of *percent 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.

Figure 7: Scenario Variables in Levels and Percent Changes



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

Figure 7 provides examples of the levels approach and the percent 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 percent changes in the stock market (shown in blue) mirror the path of percent 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. The type of transformation selected is generally based on the 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. The unemployment rate is typically updated using the shift method. This ensures that the percentage point change in the rate remains the same, and that transformation is used by FLARE. 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.

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 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. Securities' valuation losses (e.g., AOCI) is one such improvement currently being researched. Second, to bring more depth to FLARE as a macroprudential tool, the current funding shock overlay could be improved and other feedback loops such as fire sales could be modeled. Further developments will keep a broad outlook to any vulnerability that may pose a risk to banking system resiliency.

References

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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*	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 stress testing 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 real estate
All other net charge-offs
Credit card
Other consumer
Commercial and industrial
Leases
Foreign government
Agriculture
Other