Dodd-Frank Act Stress Test 2020: Supervisory Stress Test Methodology

March 2020

Board of Governors of the Federal Reserve System

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Executive Summary

This document provides details about the models developed or selected by the Federal Reserve for use in the supervisory stress test with the aim of further increasing the transparency of supervisory models and results.

Since the inception of the supervisory stress test, the Board of Governors of the Federal Reserve System (Board) has gradually increased the breadth of its public disclosures, which allows the public to evaluate the fundamental soundness of the supervisory stress test and can increase public and market confidence in the results of the assessment. The Board has sought and received feedback regarding the transparency of the supervisory stress test from the public during routine reviews of its stress testing and capital planning programs.[1] In 2019, the Board finalized a set of changes to improve the public's understanding of the models used in the supervisory stress test and of the Federal Reserve's modeling processes.[2]

Disclosing additional information about the Federal Reserve's supervisory modeling process, in particular, can further enhance the credibility of the test, as supervisory models are critical inputs into the estimation of post-stress capital in the supervisory stress test. Providing certain additional details on models can facilitate the public's understanding and interpretation of the results of the stress test. The publication of certain additional information on the models that assign losses to particular positions could also help financial institutions subject to the stress test understand the capital implications of changes to their business activities. This document is designed to improve the transparency around the supervisory models, while maintaining the efficacy of the supervisory stress test.[3]

This document is organized into the following sections: "Approach to Supervisory Model Development and Validation" provides an overview of the general approach to supervisory model development and validation in stress testing. "Overview of Modeling Framework" summarizes the supervisory modeling framework and methodology. "Descriptions of Supervisory Models" includes detailed descriptions of the supervisory stress test models. "Modeled Loss Rates" contains additional disclosures for certain material portfolios, including modeled loss rates on pools of loans and loss rates associated with portfolios of hypothetical loans. Finally, "Appendix A: Model Changes for the 2020 Supervisory Stress Test" describes a comprehensive list of supervisory model changes effective for the 2020 supervisory stress test.

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1 For example, in July of 2019, the Federal Reserve hosted "Stress Testing: A Discussion and Review," which was a conference that brought together academics, regulators, bankers, and other stakeholders to discuss the transparency and effectiveness of the stress tests.

2 See 84 Fed. Reg. 6651, 6664, 6784 (Feb. 28, 2019).

3 The Federal Reserve acknowledges that there are costs associated with full transparency of supervisory models. The disclosures in this document have been developed to increase the transparency of the supervisory stress test while maintaining its dynamism and effectiveness. See 84 Fed. Reg. 6651, 6664, 6784 (Feb. 28, 2019).

Introduction

The Federal Reserve promotes a safe, sound, and efficient banking and financial system that supports the growth and stability of the U.S. economy through its supervision of bank holding companies (BHCs), U.S. intermediate holding company (IHC) subsidiaries of foreign banking organizations, savings and loan holding companies, and state member banks.

The Federal Reserve has established frameworks and programs for the supervision of its largest and most complex financial institutions to achieve its supervisory objectives, incorporating lessons learned from the 2007–09 financial crisis and in the period since. As part of these supervisory frameworks and programs, the Federal Reserve assesses whether BHCs with $100 billion or more in total consolidated assets and U.S. IHCs (together, firms) are sufficiently capitalized to absorb losses during stressful conditions while meeting obligations to creditors and counterparties and continuing to be able to lend to households and businesses. The Board first adopted rules implementing these frameworks and programs in October 2012 and most recently modified these rules in March 2020.[4]

Each year, the Federal Reserve publicly discloses the results of its supervisory stress test. These disclosures include revenues, expenses, losses, pre-tax net income, and capital ratios under adverse economic and financial conditions projected by the Federal Reserve. The Federal Reserve projects these components using a set of models developed or selected by the Federal Reserve that take as inputs the Board's scenarios and firm-provided data on firms' financial conditions and risk characteristics.

[4] On October 10, 2019, the Board finalized a rule to amend its prudential standards to exempt firms with total consolidated assets of less than $100 billion from the supervisory stress test and to subject certain firms with total consolidated assets between $100 billion and $250 billion to the supervisory stress test requirements on a two-year cycle (84 Fed. Reg. 59032 (Nov. 1, 2019)). Firms with $250 billion or more in total consolidated assets or material levels of other risk factors remain subject to the supervisory stress test requirements on an annual basis.

On March 4, 2020, the Board approved a rule to simplify its capital rules for large banks through the establishment of the stress capital buffer, which integrates the Board's stress test results with its non-stress capital requirements (85 Fed. Reg. 15576 (Mar. 18, 2020)).

Approach to Supervisory Model Development and Validation

The Federal Reserve's supervisory stress test models are developed or selected by Federal Reserve staff and are intended to capture how firms' net income and other components of regulatory capital would be affected by the macroeconomic and financial conditions described in the supervisory scenarios, given the characteristics of their loan and securities portfolios; trading and private equity exposures and counterparty exposures from derivatives and securities financing transactions (SFTs); business activities; and other relevant factors. In developing supervisory models, Federal Reserve staff draws on economic research and industry practice in modeling these effects on revenues, expenses, and losses. The supervisory models are evaluated by an independent team of Federal Reserve model reviewers.

In February 2019, the Board finalized a Stress Testing Policy Statement that includes modeling principles and policies that guide the development, implementation, validation, and use of supervisory models, after inviting and incorporating comments on these principles and policies from the public.[5] Consistent with the principles described in the policy statement, the Federal Reserve designed the system of models to result in projections that are (1) from an independent supervisory perspective; (2) forward-looking; (3) consistent and comparable across covered companies; (4) generated from simple approaches, where appropriate; (5) robust and stable; (6) conservative; and (7) able to capture the effect of economic stress.

The Federal Reserve's models rely on detailed portfolio data provided by firms but generally do not rely on models or estimates provided by firms, consistent with the modeling principle that emphasizes an independent perspective. This framework is unique among regulators in its use of independent estimates of losses and revenues under stress, enables the Federal Reserve to provide the public and firms with credible, independent assessments of each firm's capital adequacy under stress, and helps instill public confidence in the banking system.

The Federal Reserve generally develops its models under an industry-level approach calibrated using data from many financial institutions. This approach reflects modeling principles that favor models resulting in consistent, comparable, and forward-looking projections. The Federal Reserve models the response of specific portfolios and instruments to variations in macroeconomic and financial scenario variables such that differences across firms are driven by differences in firm-specific input data, as opposed to differences in model parameters and specifications. As a result, two firms with the same portfolio receive the same results for that portfolio in the supervisory stress test, facilitating the comparability of results. In addition, the industry-level approach promotes a forward-looking stress test, as it results in models that do not assume that historical patterns will necessarily continue into the future for individual firms. These policies also help to ensure that consistent and comparable supervisory models are forward-looking, robust, and stable.

In general, the Federal Reserve only employs firm-specific fixed effects and vintage indicator variables when there are significant structural market shifts or other unusual factors for which supervisory models cannot otherwise account. For example, the Federal Reserve may use

[5] See 84 Fed. Reg. 6664 (Feb. 28, 2019).

firm-specific indicator variables, firm-provided estimates, or third-party models or data in instances in which it is not possible or appropriate to create a supervisory model for use in the stress test, including when supervisory data are insufficient to support an independently modeled estimate of losses or revenues.[6] However, the Federal Reserve does not adjust supervisory projections for individual firms or implement firm-specific overlays to model results used in the supervisory stress test. This policy ensures that the supervisory stress test results are determined solely by supervisory models and firm-specific input data.

Policies Related to Model Risk Management, Governance, and Validation

Supervisory model risk management is key to the credibility of the supervisory stress test process. The supervisory model risk management program helps to ensure adherence to consistent development principles, conducts independent model validation, maintains a supervisory model governance structure, and communicates the state of model risk to the members of the Board of Governors on a regular basis. External parties have reviewed several aspects of the Federal Reserve's supervisory stress testing program, including its model risk management framework.

Structure of Model Development and Risk Management Oversight Groups

The Model Oversight Group (MOG), the System Model Validation group, and the Supervisory Stress Test Model Governance Committee are collectively responsible for managing the Federal Reserve's supervisory stress test models and any associated model risks.

The MOG, a national committee of senior staff drawn from across the Federal Reserve System, oversees supervisory model development, implementation, and use. The MOG strives to produce supervisory stress test results that reflect likely outcomes under the supervisory scenarios and ensures that model design across the system of supervisory stress test models results in projections that are consistent with the Federal Reserve's supervisory modeling policies.

The MOG also reviews the results of common model risk management tools[7] and assesses potential model limitations and sources of uncertainty surrounding final outputs. A dedicated subgroup of the MOG assists in these efforts and also reviews, assesses, and implements industry standards and best practices for model risk management in stress testing operations. This group is composed of Federal Reserve staff and helps set internal policies, procedures, and standards related to the management of model risk stemming from individual models, as

6 For example, the models to project components of pre-provision net revenue (PPNR) feature firm-specific indicator variables because available data are not sufficiently granular and a firm's own history, after controlling for structural changes over time, is proven to be more predictive of the firm's revenues and expenses under stress than industry-level history. In addition, in order to project trading and counterparty losses, sensitivities to risk factors and other information generated by firms' internal models are used. In cases in which firm-provided or third-party model estimates are used, the Federal Reserve monitors the quality and performance of the estimates through targeted examination, additional data collection, or benchmarking.

7 Those tools include the use of benchmark models, where applicable, performance testing and monitoring, and sensitivity analysis, which isolates the effect of a change in one model input on the eventual model output. The System Model Validation group examines these tools as part of its process and may recommend modifications to those tools to improve their comprehensiveness.

well as the system of supervisory models used to project post-stress capital ratios. In this way, the Federal Reserve's approach reflects the same standards of model risk management that banking organizations are also expected to follow.

Each year, an independent System Model Validation group validates the supervisory stress test models. The System Model Validation group is composed of dedicated full-time staff members not involved in supervisory modeling, supplemented by subject matter experts from across the Federal Reserve System. This group's model validation process includes reviews of model performance, conceptual soundness, and the processes, procedures, and controls used in model development, implementation, and the production of results. For each model, the group annually assesses the model's reliability based on its underlying assumptions, theory, and methods and determines whether any issues require remediation as a result of that assessment. The Model Validation Council, a group of academic experts not affiliated with the Federal Reserve, provides advice to the Federal Reserve on the validation program and activities.[8]

The MOG and the System Model Validation group are overseen by the director of the Board's Division of Supervision and Regulation. The Supervisory Stress Test Model Governance Committee—a committee of senior Federal Reserve staff that includes representatives from model development, implementation, validation, and scenario design—advises the director on matters related to the governance of supervisory stress test models and facilitates the director's oversight role by providing a regular forum to present and discuss relevant issues. This committee also identifies key model risk issues in the supervisory stress testing program and elevates these issues to the director and the members of the Board of Governors. The committee produces an annual formal communication to the members of the Board of Governors on the structure of the supervisory stress test model risk management program and the state of model risk as determined by each year's model validation process.

External Review of Model Development and Validation Programs

Both internal and external parties have reviewed the development and validation of the supervisory stress test models. In 2015, the Federal Reserve Office of the Inspector General (OIG) reviewed model validation activities and recommended improvements in staffing, model inventories, and communication with management.[9] The Federal Reserve has implemented each of the OIG's recommendations, and the OIG has formally closed its findings. Additionally, in 2016, the Government Accountability Office (GAO) issued a report on the Federal Reserve's stress testing and capital planning programs.[10] The GAO recognized in its report that the Federal Reserve's stress testing program has played a key role in evaluating and maintaining the stability of the U.S. financial system since the most recent financial crisis. The GAO report included five recommendations as to how the Federal Reserve could improve its

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[8] See Board of Governors of the Federal Reserve System, "Federal Reserve Board Announces the Formation of the Model Validation Council," press release, April 20, 2012, https://www.federalreserve.gov/newsevents/pressreleases/bcreg20120420a.htm.

[9] See Board of Governors of the Federal Reserve System and Consumer Financial Protection Bureau, Office of Inspector General, *The Board Identified Areas of Improvement for Its Supervisory Stress Testing Model Validation Activities, and Opportunities Exist for Further Enhancement,* Evaluation Report 2015-SR-B-018 (Washington: Board of Governors and CFPB, OIG, October 2015), https://oig.federalreserve.gov/reports/board-supervisory-stress-testing-model-validation-reissue-oct2015.pdf.

[10] See Government Accountability Office, "Additional Actions Could Help Ensure the Achievement of Stress Test Goals," (Washington: GAO, November 2016), https://www.gao.gov/assets/690/681020.pdf.

model risk management and ensure that its decisions are informed by a comprehensive understanding of model risk. In response, the Federal Reserve has already addressed a number of these recommendations and continues to enhance its stress test model risk management program as consistent with other GAO recommendations.

Data Inputs

The Federal Reserve develops and implements the models with data it collects on regulatory reports as well as proprietary third-party industry data.[11]

Certain projections rely on the Consolidated Financial Statements for Holding Companies (FR Y-9C) regulatory report, which contains consolidated income statement and balance sheet information for each firm. The FR Y-9C also includes off-balance sheet items and other supporting schedules, such as the components of RWAs and regulatory capital.

Most of the data used in the Federal Reserve's stress test projections are collected through the Capital Assessments and Stress Testing (FR Y-14) information collection, which includes a set of annual, quarterly, and monthly schedules (FR Y-14A/Q/M).[12] These reports collect detailed data on pre-provision net revenue (PPNR), loans, securities, trading and counterparty risk, and losses related to operational-risk events.

Firms are required to submit detailed loan and securities information for all material portfolios. The definition of materiality is based on a firm's size and complexity. Portfolio categories are defined in the FR Y-14M and FR Y-14Q instructions. Each firm has the option to either submit or not submit the relevant data schedule for a given portfolio that does not meet the materiality threshold as defined in the instructions. If a firm does not submit data on its immaterial portfolio(s), the Federal Reserve will assign to that portfolio the median loss rate estimated across the set of firms with material portfolios.

While firms are responsible for ensuring the completeness and accuracy of data reported in the FR Y-14 information collection, the Federal Reserve makes efforts to validate firm-reported data and requests resubmissions of data where errors are identified. If data quality remains deficient after resubmission, the Federal Reserve applies conservative assumptions to a particular portfolio or to specific data, depending on the severity of deficiencies. For example, if the Federal Reserve deems the quality of a firm's submitted data too deficient to

[11] In connection with the supervisory stress test, and in addition to the models developed and data collected by federal banking regulators, the Federal Reserve uses proprietary models or data licensed from the following providers:

Andrew Davidson & Co., Inc.; Black Knight Financial Services; Bloomberg Finance LP; CBRE Econometric Advisors; CoreLogic Inc.; Cox Enterprises, Inc.; Equifax Information Services LLC; Federal Home Loan Mortgage Corporation; Haver Analytics; ICE Data Services; IHS Markit Ltd.; Mergent, Inc.; Moody's Analytics, Inc.; Moody's Investors Service, Inc.; Morningstar, Inc.; Municipal Securities Rulemaking Board; Real Capital Analytics, Inc.; Refinitiv; RiskMetrics Solutions, LLC; S&P Global Market Intelligence; and The World Bank.

In addition, with respect to the global market shock component of the severely adverse scenario, the Federal Reserve uses proprietary data licensed from the following providers: Bloomberg Finance LP; ICE Data Services; IHS Markit Ltd; JPMorgan Chase & Co.; Markit Group Limited; Moody's Analytics, Inc.; and RiskMetrics Solutions, LLC. Notes regarding scenario variable data can be found in Board of Governors of the Federal Reserve System, *2020 Supervisory Scenarios for Annual Stress Tests Required under the Dodd-Frank Act Stress Testing Rules and the Capital Plan Rule* (Washington: Board of Governors, February 2020), 15–16, https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20200206a1.pdf.

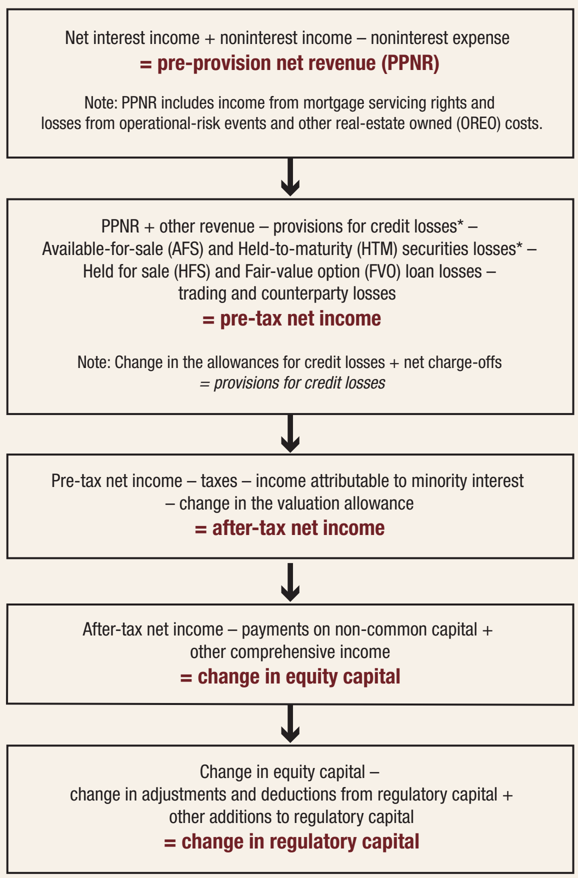
[12] The FR Y-14 report forms and instructions are available on the Board's website at https://www.federalreserve.gov/apps/reportforms/default.aspx.

produce a supervisory model estimate for a particular portfolio, then the Federal Reserve assigns a high loss rate (e.g., 90th percentile) or a conservative PPNR rate (e.g., 10th percentile) to the portfolio balances based on supervisory projections of portfolio losses or PPNR estimated for other firms. If data that are direct inputs to supervisory models are missing or reported erroneously but the problem is isolated in such a way that the existing supervisory framework can still be used, the Federal Reserve assigns a conservative value (e.g., 10th or 90th percentile) to the specific data based on all available data reported by firms. These assumptions are consistent with the Federal Reserve's principle of conservatism and policies on the treatment of immaterial portfolios and missing or erroneous data.

Overview of Modeling Framework

The Federal Reserve estimates the effect of supervisory scenarios on the regulatory capital ratios of firms participating in the supervisory stress test by projecting net income and other components of regulatory capital for each firm over a nine-quarter projection horizon. Projected net income, adjusted for the effect of taxes, is combined with non-common capital action assumptions and other components of regulatory capital to produce post-stress capital ratios. The Federal Reserve's approach to modeling post-stress capital ratios generally follows U.S. generally accepted accounting principles (GAAP) and the regulatory capital framework.[13] Figure 1 illustrates the framework used to calculate changes in net income and regulatory capital.

Figure 1. Projecting net income and regulatory capital



*For firms that have adopted ASU 2016-13, the Federal Reserve intends to incorporate its projection of expected credit losses on securities in the Allowance for Credit Losses, in accordance with Financial Accounting Standards Board (FASB), *Financial Instruments–Credit Losses* (Topic 326), FASB Accounting Standards Update (ASU) 2016-13 (Norwalk, Conn.: FASB, June 2016).

[13] See 12 C.F.R. pt. 217 (2019).

Projecting Pre-tax Net Income

The Federal Reserve calculates projected pre-tax net income for the firms subject to the supervisory stress test by combining projections of revenue, expenses, provisions for credit losses, and other losses, including

- PPNR;
- provisions for credit losses;
- losses on loans held for sale (HFS) or for investment and measured under the fair-value option (FVO);
- credit losses on investment securities in the available-for-sale (AFS) and held-to-maturity (HTM) portfolios;[14]
- losses on market risk exposures, credit valuation adjustment (CVA), and incremental default risk (IDR) for firms subject to the global market shock; and
- losses from a default of the largest counterparty for firms with substantial trading, processing, or custodial operations.

The Federal Reserve projects these components of pre-tax net income using supervisory models that take the Board's scenarios and firm-provided data as inputs. The projections are based on the assumption that firms' balance sheets remain unchanged throughout the projection period. Macroeconomic variables used in select supervisory models vary across geographic locations (e.g., by state or by county). The Federal Reserve projects the paths of these variables as a function of aggregate macroeconomic variables included in the Board's scenarios.

Pre-provision Net Revenue

PPNR is defined as net interest income (interest income minus interest expense) plus noninterest income minus noninterest expense. Consistent with U.S. GAAP, the projection of PPNR includes projected losses due to operational-risk events and expenses related to the disposition of real-estate-owned properties.[15]

The Federal Reserve models most components of PPNR using a suite of models that generally relate specific revenue and non-provision-related expenses to the characteristics of firms and to macroeconomic variables. These include eight components of interest income, seven components of interest expense, six components of noninterest income, and three components of noninterest expense.

The Federal Reserve separately models losses from operational risk and other real-estate-owned (OREO) expenses. Operational risk is defined as "the risk of loss resulting from inad-

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[14] For firms that have adopted ASU 2016-13, the Federal Reserve intends to incorporate its projection of expected credit losses on securities in the Allowance for Credit Losses, in accordance with Financial Accounting Standards Board (FASB), *Financial Instruments–Credit Losses* (Topic 326), FASB Accounting Standards Update (ASU) 2016-13 (Norwalk, Conn.: FASB, June 2016).

[15] PPNR projections do not include debt valuation adjustment, which is not included in regulatory capital.

equate or failed internal processes, people and systems or from external events."[16] OREO expenses are those expenses related to the disposition of real-estate-owned properties and stem from losses on first-lien mortgages.

Loan Losses and Provisions on the Accrual Loan Portfolio

The Federal Reserve projects 13 quarters of losses on loans in the accrual loan portfolio using one of two modeling approaches: the expected-loss framework or the net charge-off approach.

For certain loans, expected losses under the macroeconomic scenario are estimated by projecting the probability of default (PD), loss given default (LGD), and exposure at default (EAD) for each quarter of the projection horizon. Expected losses in each quarter are the product of these three components.

Losses are modeled under the expected-loss framework for the following loan categories:

- corporate loans, including graded commercial and industrial (C&I) loans, agricultural loans, domestic farm loans, international farm loans, loans to foreign governments, loans for purchasing and carrying securities, other non-consumer loans, and other leases
- commercial real estate (CRE) loans, including domestic and international non-owner-occupied multifamily or nonfarm, nonresidential property loans and construction and land development (C&LD) loans
- domestic first-lien residential mortgages
- domestic home equity loans (HELs) and home equity lines of credit (HELOCs)
- domestic credit cards
- domestic auto loans

The net charge-off approach projects losses over the projection horizon using models that capture the historical behavior of net charge-offs as a function of macroeconomic and financial market conditions and loan portfolio characteristics. The Federal Reserve models losses under the net charge-off approach for other consumer loans, business and corporate credit card loans, small-business loans, student loans, and international retail loans.

Losses on the accrual loan portfolio flow into net income through provisions for loan and lease losses. Generally, provisions for loan and lease losses for each quarter equal projected loan losses for the quarter plus the change in the allowance needed to cover the subsequent four quarters of expected loan losses, taking into account the allowance established by the firm as of the effective date of the stress test exercise.[17]

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[16] See Basel Committee on Banking Supervision, *International Convergence of Capital Measurement and Capital Standards* (Basel, Switzerland: BCBS, June 2004), 149, https://www.bis.org/publ/bcbs107.pdf.

[17] To reduce uncertainty, allow for better capital planning at affected firms, and gather additional information on the impact of the current expected credit loss methodology (CECL), the Federal Reserve plans to maintain the framework used prior to the adoption of CECL for calculating allowances on loans in the supervisory stress test for the 2020 and 2021 supervisory stress test cycles. See Board of Governors of the Federal Reserve System, "Statement on the Current Expected Credit Loss Methodology (CECL) and Stress Testing," press release, December 21, 2018, https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20181221b1.pdf.

The Federal Reserve assumes that the allowance at the end of each quarter covers projected loan losses for four quarters into the future. The supervisory estimate of the allowance at the start of the projection horizon, which is based on projected losses under the severely adverse scenario, may differ from a firm's established allowance at the beginning of the projection horizon, which is based on the firm's estimate of losses on the effective date of the stress test. Any difference between the supervisory calculation of the allowance and the firm's reported allowance at the beginning of the projection horizon is linearly smoothed into the Federal Reserve's provisions projection over the nine quarters.

Losses on Loans Measured on a Fair-Value Basis

Certain loans are accounted for on a fair-value basis instead of on an accrual basis. For example, if a loan is accounted for using the FVO, it is marked to market, and the accounting value of the loan changes as market risk factors and fundamentals change. Similarly, loans that are held for sale are accounted for at the lower of cost or market value.

The models for these asset classes project gains and losses on the banks' FVO/HFS loan portfolios over the nine-quarter projection horizon, net of any hedges, by applying the scenario-specific path of interest rates and credit spreads to loan yields.

Losses are modeled under this approach for the following loan categories:

- FVO/HFS C&I loans
- FVO/HFS CRE loans
- FVO/HFS residential mortgages, student loans, auto loans, and credit cards

Gains and losses on HFS C&I and CRE loans are estimated using a model specific to those asset classes. Gains and losses on FVO/HFS retail loans are modeled separately.

Losses on Securities in the Available-for-Sale and Held-to-Maturity Portfolios

The Federal Reserve estimates two types of losses on AFS or HTM securities related to investment activities.[18] First, for securities classified as AFS, projected changes in the fair value of the securities due to changes in interest rates and other factors will result in unrealized gains or losses that are recognized in capital for some firms through other comprehensive income (OCI).[19] Second, credit losses on the security may be recorded. With the exception of certain government-backed obligations, both AFS and HTM securities are at risk of incurring credit losses.[20] The models project security-level credit losses, using as an input the projected fair value for each security over the nine-quarter projection horizon under the macroeconomic scenarios.

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[18] This portfolio does not include securities held for trading. Losses on these securities are projected by the model that projects gains and losses on trading exposures.

[19] Other comprehensive income is accounted for outside of net income. Under regulatory capital rules, accumulated OCI (AOCI) that arises from unrealized changes in the value of AFS securities must be incorporated into common equity tier 1 capital for firms subject to the advanced approaches and other firms that do not opt out of including AOCI in regulatory capital.

[20] Certain government-backed securities, such as U.S. Treasuries, U.S. government agency obligations, U.S. government agency or government-sponsored enterprise (GSE) mortgage-backed securities, Federal Family Education Loan Program student loan asset-backed securities, and pre-refunded municipal bonds, are assumed not to be subject to credit losses.

Securities at risk of credit losses include the following securitizations and direct debt obligations:

- corporate debt securities
- sovereign debt securities (other than U.S. government obligations)
- municipal debt securities
- mortgage-backed, asset-backed, collateralized loan obligation (CLO), and collateralized debt obligation (CDO) securities

Gains or Losses on the Fair Value of Available-for-Sale Securities

The fair value of securities in the AFS portfolio may change in response to the macroeconomic scenarios. Under U.S. GAAP, unrealized gains and losses on AFS securities are reflected in accumulated OCI (AOCI) but do not flow through net income.[21] Under the regulatory capital rule, AOCI must be incorporated into common equity tier 1 capital (CET1) for certain firms.[22] The incorporation of AOCI in regulatory capital is described in "Calculation of Regulatory Capital Ratios" below.

Unrealized gains and losses are calculated as the difference between each security's fair value and its amortized cost. The amortized cost of each AFS security is equivalent to the purchase price of a debt security, which is periodically adjusted if the debt security was purchased at a price other than par or face value, has a principal repayment, or has an impairment recognized in earnings.[23]

OCI losses from AFS securities are computed directly from the projected change in fair value, taking into account credit losses and applicable interest-rate hedges on securities. All debt securities held in the AFS portfolio are subject to OCI losses, including

- U.S. Treasuries;
- U.S. agency securities;
- corporate debt securities;
- sovereign debt securities;
- municipal debt securities; and
- mortgage-backed, asset-backed, CLO, and CDO securities.

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[21] Unrealized gains and losses on equity securities are recognized in net income and affect regulatory capital for all firms. See Financial Accounting Standards Board (FASB), *Financial Instruments—Overall* (Subtopic 825-10), FASB Accounting Standards Update (ASU) 2016-01 (Norwalk, Conn.: FASB, January 2016).

[22] The Board amended its prudential standards to allow firms with total consolidated assets of less than $700 billion and cross-jurisdictional activity of less than $75 billion to opt out of including AOCI in regulatory capital (84 Fed. Reg. 59230 (Nov. 1, 2019)).

[23] The fair value of each AFS security is projected over the nine-quarter projection horizon using either a present-value calculation, a full revaluation using a security-specific discounted cash flow model, or a duration-based approach, depending on the asset class.

Losses on Trading and Private Equity Exposures and Credit Valuation Adjustment

The global market shock, which applies to a subset of firms, is a set of hypothetical shocks to market values and risk factors that affect the market value of firms' trading and private equity positions.[24] The design of the global market shock component differs from the design of the nine-quarter macroeconomic scenario in that it assumes the losses are incurred at the start of the projection horizon rather than gradually over nine quarters. The assumption is consistent with the Federal Reserve's model design principles that emphasize the use of conservative and forward-looking projections, particularly in the face of uncertainty. The timing is based on an observation that market dislocations can happen rapidly and unpredictably any time under stress conditions. Applying the global market shock in the first quarter of the projection horizon ensures that potential losses from trading and counterparty exposures are incorporated into trading companies' capital ratios at all points in the projection horizon.

The trading and private equity model generates loss estimates related to trading and private equity positions under the global market shock. In addition, the global market shock is applied to firm counterparty exposures to generate losses due to changes in CVA.

The trading and private equity model covers a wide range of firms' exposures to asset classes such as public equity, foreign exchange, interest rates, commodities, securitized products, traded credit (e.g., municipals, auction rate securities, corporate credit, and sovereign credit), private equity, and other fair-value assets. Loss projections are constructed by applying movements specified in the global market shock to market values of firm-provided positions and risk factor sensitivities.[25]

Incremental Default Risk

The Federal Reserve separately estimates the risk of losses arising from a jump-to-default of issuers of debt securities in the trading book, in excess of mark-to-market losses calculated by the trading model. Trading losses associated with IDR account for concentration risk in agencies, trading book securitization positions, and corporate, sovereign, and municipal bonds. These losses are applied in each of the nine quarters of the projection horizon.

Largest Counterparty Default Losses

The largest counterparty default (LCPD) scenario component is applied to firms with substantial trading or custodial operations. The LCPD captures the risk of losses due to an unexpected default of the counterparty whose default on all derivatives and SFTs would generate the largest stressed losses for a firm.

Consistent with the Federal Reserve's modeling principles, losses associated with the LCPD component are recognized in the first quarter of the projection horizon.

[24] The global market shock in the 2020 supervisory stress test applies to firms that have aggregate trading assets and liabilities of $50 billion or more, or trading assets and liabilities equal to or greater than 10 percent of total consolidated assets. See 82 Fed. Reg. 59608 (Dec. 15, 2017).

[25] The trading model is also used to calculate gains or losses on firms' portfolios of hedges on credit valuation adjustment exposures (CVA hedges).

Balance Projections and the Calculation of Regulatory Capital Ratios

Balance Sheet Items and Risk-Weighted Assets

The Federal Reserve generally projects that a firm takes actions to maintain its current level of assets, including its securities, trading assets, and loans, over the projection horizon. The Federal Reserve assumes that a firm's risk-weighted assets (RWAs) and leverage ratio denominators remain unchanged over the projection horizon except for changes primarily related to items subject to deduction from regulatory capital or due to changes to the Board's regulations.[26]

Calculation of Regulatory Capital Ratios

The five regulatory capital measures that are included in the supervisory stress test are the (1) CET1, (2) tier 1 risk-based capital, (3) total risk-based capital, (4) tier 1 leverage, and (5) supplementary leverage ratios. A firm's regulatory capital ratios are calculated in accordance with the Board's regulatory capital rules using Federal Reserve projections of pre-tax net income and other scenario-dependent components of the regulatory capital ratios.

Pre-tax net income and the other scenario-dependent components of the regulatory capital ratios are combined with additional information, including assumptions about taxes and capital distributions, to calculate post-stress regulatory capital. In that calculation, the Federal Reserve first adjusts pre-tax net income to account for taxes and other components of net income, such as income attributable to minority interests, to arrive at after-tax net income.[27]

The Federal Reserve calculates the change in equity capital over the projection horizon by combining projected after-tax net income with changes in OCI, assumed capital distributions, and other components of equity capital. The path of regulatory capital over the projection horizon is calculated by combining the projected change in equity capital with the firm's starting capital position and accounting for other adjustments to regulatory capital specified in the Board's regulatory capital framework.[28]

The denominator of each firm's regulatory capital ratios, other than the leverage ratios, is calculated using the standardized approach for calculating RWAs for each quarter of the projection horizon, in accordance with the transition arrangements in the Board's capital rules.[29]

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[26] See 12 C.F.R. pts. 217, 225, and 252 (2020); the Federal Register notice is available on the Board's website at https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20200304a2.pdf. For additional information, see also Board of Governors of the Federal Reserve System, "Federal Reserve Board Approves Rule to Simplify Its Capital Rules for Large Banks, Preserving the Strong Capital Requirements Already in Place," press release, March 4, 2020, https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200304a.htm.

[27] The Federal Reserve applies a consistent tax rate of 21 percent to pre-tax net income and accounts for deferred tax assets.

[28] The regulatory capital framework specifies that regulatory capital ratios account for items subject to adjustment or deduction in regulatory capital, limits the recognition of certain assets that are less loss-absorbing, and imposes other restrictions.

[29] 12 C.F.R. pt. 217, subpt. G (2019).

Descriptions of Supervisory Models

Pre-provision Net Revenue

PPNR is defined as net interest income (interest income minus interest expense) plus non-interest income minus noninterest expense, including losses from operational-risk events and OREO expenses.[30]

Core Components of PPNR

The Federal Reserve projects components of PPNR, other than operational-risk and OREO losses, using a suite of models that generally relate specific revenue and non-provision-related expenses to firm characteristics and macroeconomic variables. These models are primarily estimated using data from the FR Y-9C and FR Y-14Q and data on historical economic conditions. When choosing the level of detail at which to model these core components of PPNR, the Federal Reserve considers the economic factors driving each component and other factors, such as the statistical properties of the individual income or the expense component and data availability. The PPNR components are projected using firm-reported data and economic conditions defined in the Federal Reserve's supervisory stress test scenarios.

The key firm characteristics that affect projected revenues and expenses include

- average historical values of the income or expense components and
- composition and size of assets and liabilities.

Revenues and expenses projected by the models vary based on changes in the economic conditions over the nine quarters of the projection horizon. Those include

- interest rates,
- stock market returns and volatility,
- corporate bond spreads, and
- GDP growth.

The Federal Reserve uses separate models to project 24 PPNR components:[31]

- The eight modeled components of interest income include interest income on (1) federal funds and repurchase agreements, (2) interest-bearing balances, (3) loans, (4) mortgage-backed securities, (5) other securities, (6) trading assets, (7) U.S. Treasuries, and (8) all other interest income.
- The seven modeled components of interest expense include interest expense on (9) domestic time deposits, (10) federal funds and repurchase agreements, (11) foreign deposits,

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[30] OREO expenses are based on losses projected by the first-lien mortgage model, which is discussed in the "Loan Losses and Provisions on the Accrual Loan Portfolio" section.

[31] In modeling PPNR, the Federal Reserve makes adjustments to eliminate or minimize potential double-counting of losses. For example, in the models of core PPNR components, the Federal Reserve adjusts historical data series to exclude losses from operational-risk events and OREO expenses. In addition, the modeling approach for trading revenue limits the influence of severe market events that are separately captured in the global market shock.

(12) other domestic deposits, (13) subordinated debt, (14) trading liabilities and other borrowed money, and (15) all other interest expenses.

- The six modeled components of noninterest income include (16) trading revenue and the following five components of noninterest, nontrading income: (17) fiduciary income and insurance and banking fees, (18) investment banking fees, (19) net servicing fees, (20) service charges on deposits, and (21) all other noninterest income.
- Finally, the three modeled components of noninterest expense include (22) compensation expense, (23) fixed asset expense, and (24) all other noninterest expense, excluding losses from operational-risk events and OREO expenses.

The types of models used to project various components of PPNR include

- autoregressive models that relate the components of a firm's revenues and non-provision-related expenses, expressed as a share of the relevant asset or liability balance, to macroeconomic variables, recent past values of the revenue or expense ratio, firm characteristics, and other controls;
- aggregate models that relate industry revenue or expense to macroeconomic variables and then allocate industry revenue or expense to each firm based on a measure of the firm's market share;
- simple nonparametric models based on recent firm-level performance; and
- structural models that use granular data on individual positions.

For all models, excluding the structural models that use granular data on individual positions, each component of PPNR is normalized by a relevant asset or liability balance (see table 1). For example, interest income on U.S. Treasuries is divided by the value of U.S. Treasuries.

The Federal Reserve models 20 of the 24 core PPNR components using an autoregressive model specification based on pro-forma historical regulatory data drawn primarily from firms' quarterly FR Y-9C filings.

Each autoregressive model includes both individual firm fixed effects and a trailing multiyear fixed effect to capture each firm's average performance in recent years.[32] The autoregressive term in each model is the mean of the dependent variable calculated over the past four quarters. As a result, projections for these 20 PPNR components converge over time toward the firm's recent average performance for that revenue or expense category, while still allowing for variation in response to changes in macroeconomic conditions. Recent changes in a firm's business model or performance are reflected in the projections through both changes in the recent average PPNR ratios and changes in lagged revenue or expense ratios.

[32] The trailing multiyear fixed effect interacts a firm-specific fixed effect with an indicator variable that takes the value of 1 for the past several years. See Appendix A for additional details. Firm-specific fixed effects used in the PPNR models are indicator variables that account for unobserved characteristics of the individual firm. These fixed effects aim to capture individual firm characteristics and differences in business models that cannot be accounted for by firm balance sheet variables.

The models are generally specified according to the following equation:

$$Ratio(b,t) = f\left(\sum_{j=1}^{j=4} \frac{Ratio(b,t-j)}{4}, FE(b), FE(b)*Ind(T-Q<t\leq T), Z(t), X(b,t)\right) \quad (1)$$

where b represents the firm, t represents time, $Ratio(b,t)$ represents the component ratio, $\sum_{j=1}^{j=4} \frac{Ratio(b,t-j)}{4}$ represents the mean of the lagged component ratio over the past four quarters where j is the lagged quarter, $FE(b)$ represents the fixed effect for firm b, $FE(b)*Ind(T-Q<t\leq T)$ represents the trailing multiyear fixed effect for the last Q quarters for firm b where T is the end of the estimation period, $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios, and $X(b,t)$ includes firm characteristics and other controls, such as seasonal factors in some equations.

The specific macroeconomic variables that enter each regression model differ across equations and are chosen based on statistical predictive power and economic theory. For example, yields on U.S. Treasuries are key variables in the models of the interest income and expense components, while GDP growth, stock market volatility, and stock returns are featured in many of the models of the noninterest expense and noninterest income components.

Some components of PPNR are estimated separately for groups of similar firms. Because these components span a relatively broad range of business lines and borrowers, the model structure for these components allows for a different relationship between macroeconomic variables and revenues across different types of firms. Regressions are estimated separately for specific groups for noninterest income from investment banking fees, interest expense on trading liabilities and other borrowed money, trading revenue, and compensation expense.

For firms subject to the global market shock, the Federal Reserve models trading revenues in the aggregate as a function of stock market returns and changes in stock market volatility and allocates revenues to each firm based on a measure of the firm's market share. Firms' trading revenues include both changes in the market value of trading assets and fees from market-making activities. Trading revenue for this group of firms is modeled using a median regression approach to lessen the influence of extreme movements in trading revenues and thereby mitigate the double-counting of trading losses that are captured under the global market shock. Trading revenues for remaining firms are modeled in an autoregressive framework similar to that of other PPNR components.

The Federal Reserve models certain components using simple, nonparametric models. These components are highly volatile from quarter to quarter but do not exhibit a clear cyclical pattern. As a result, these components are projected as the median of the firm's ratio over the most recent eight quarters.

Finally, the Federal Reserve projects interest expense on subordinated debt using a structural model that utilizes security-level data on individual positions. In contrast to the other PPNR component models, this more granular model accounts for differences across firms in the maturity, currency denomination, coupon, and rating of subordinated debt securities. The model calculates interest expense on subordinated debt as the outstanding balance multiplied by the contractual rate for each debt security collected on the FR Y-14Q, adjusted to account for unamortized costs from subordinated debt issued at a premium or discount to its face value and to account for interest rate hedging through swap agreements. Maturing debt is assumed to be refinanced using new debt with similar characteristics.

For each component that is modeled as a ratio, the Federal Reserve multiplies the projected ratios for each firm by the relevant projected asset or liability balances to transform projections into dollar amounts.[33]

Table 1. List of variables used to construct the PPNR components

PPNR component	Normalized by
Interest income from	
Federal funds sold and securities purchased under agreements to resell	Federal funds sold and securities purchased under agreements to resell
Interest-bearing balances	Interest-bearing balances
Loans	Total loans
Mortgage-backed securities	Mortgage-backed securities
Other securities	Other securities
Trading assets	Trading assets
U.S. Treasuries	U.S. Treasuries
All other	Interest-earning assets
Interest expense from	
Domestic time deposits	Total domestic time deposits
Federal funds purchased and securities sold under agreements to repurchase	Federal funds purchased and securities sold under agreements to repurchase
Foreign deposits	Total foreign deposits
Other domestic deposits	Other domestic deposits
Subordinated debt	n/a
Trading liabilities and other borrowed money	Trading liabilities and other borrowed money
All other	Interest-bearing liabilities[1]
Noninterest income from	
Fiduciary income & insurance/banking fees	Total assets less trading assets
Investment banking fees	Total assets
Net servicing fees	Total servicing assets
Service charges on deposits	Domestic deposits
Trading revenue	Trading assets
All other	Total assets
Noninterest expense from	
Compensation	Total assets
Fixed assets	Total assets
All other	Total assets

Note: All items are sourced from the FR Y-9C, with the exception of subordinated debt.

n/a Not applicable.

1 Interest-bearing liabilities are defined as the sum of interest-bearing deposits, fed funds liabilities, trading liabilities, other borrowed money, and subordinated debt.

33 This process is not necessary for aggregating interest expense on subordinated debt, which is projected by a security-level model.

Table 2. List of key macroeconomic variables in the PPNR regression models and sources of variables

Variable	Description	Source
BBB corporate yield	ICE BBB 7-10 year bond yield index	FR supervisory scenarios
Dow Jones Total Stock Market Index	End-of-quarter value	FR supervisory scenarios
Market Volatility Index	Market Volatility Index (VIX) converted to quarterly frequency using the maximum close-of-day value in any quarter	FR supervisory scenarios
Real GDP growth	Percent change in real gross domestic product, chained (2009) dollars, expressed at an annualized rate	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	FR supervisory scenarios
3-month Treasury rate	Quarterly average of 3-month Treasury bill secondary market rate on a discount basis	FR supervisory scenarios

Note: Variables are listed alphabetically.

Losses Related to Operational-Risk Events

Operational-risk losses include losses stemming from events such as fraud, computer system failures, process errors, and lawsuits by employees, customers, or other parties.[34] The operational-risk loss model is designed to project quarterly losses over the projection horizon for each supervisory stress test scenario. The Federal Reserve estimates the model using data on economic conditions and historical data from the FR Y-14Q and FR Y-9C. The model projects losses stemming from operational-risk events using information about the size and historical operational-risk losses of the firms and economic conditions defined in the Federal Reserve's supervisory stress test scenarios. Key firm characteristics that affect projected losses include

- the size of the firm measured by total assets and
- the firm's historical operational-risk losses by operational-risk event.

The losses projected by the model vary across scenarios based on differences in the defined economic conditions over the nine quarters of the projection horizon.

Operational-risk loss estimates are derived as the average of projections from two modeling approaches: a linear regression model and a historical simulation model.[35] The regression model captures the sensitivity of operational-risk losses to changes in the macroeconomic environment; the simulation model captures the variation in operational-risk losses across types of operational-risk events.[36]

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[34] Specifically, as noted earlier, operational risk is defined as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events." See Basel Committee on Banking Supervision, *International Convergence,* in note 16.

[35] The Federal Reserve adjusts loss projections in order to account for reported losses that fall below the modeling threshold. Firms subject to the supervisory stress test have different data collection and reporting thresholds. In order to treat firms consistently, loss events below a common modeling threshold (i.e., common across firms) are excluded before estimating the regression and historical simulation models. An additional model generates add-on estimates to account for losses excluded from modeling.

[36] These types of operational-risk events include internal fraud; external fraud; employment practices and workplace safety; clients, products, and business practice; damage to physical assets; business disruption and systems failures; and execution, delivery, and process management.

The regression model projects aggregate operational-risk losses for the industry over the projection horizon and allocates those losses to firms based on their size. The model projects operational-risk losses conditional on macroeconomic factors, except for those losses due to damage to physical assets.[37] The regression model is specified as follows:

$$OpLossRatio(t) = f\left(PC(t)\right), \qquad (2)$$

where t represents time, $OpLossRatio(t)$ represents the industry aggregate loss divided by industry aggregate assets in quarter t, and $f(PC(t))$ represents the function of the first principal component of a set of macroeconomic variables, which include measures of economic activity, financial conditions, and the interest rate environment (see table 3). The share of losses allocated to a given firm is a function of the size of the firm, measured in total assets, on the effective date of the stress test.

The historical simulation model projects operational-risk losses for each firm and for each of the seven operational-risk categories identified in the Board's regulatory capital rule. The model accounts for large and infrequent operational-risk losses by projecting loss frequency (number of loss events) and severity (dollar value of each loss event) separately.[38] The tails of the loss severity and the loss frequency distributions are informed by historical industry loss severity and loss frequency amounts scaled to the assets of individual firms, while the bodies of these distributions are informed by each firm's historical loss severity and loss frequency. Frequency and severity are then combined to form an unconditional loss distribution.[39] The projected nine-quarter loss under the supervisory severely adverse scenario corresponds to the loss at a percentile related to the frequency of severe recessions.[40] Total projected operational-risk losses are calculated as the sum of projected losses for each operational-risk event type.

Table 3. List of key variables in the operational-risk model and sources of variables

Variable	Description	Variable type	Source
All Models			
Loss	Operational-risk loss incurred by a firm in a quarter	Firm characteristic	FR Y-14Q
Total assets	Total assets of a firm at the end of the quarter	Firm characteristic	FR Y-9C

(continued)

[37] Losses due to damage to physical assets are generally not dependent on the macroeconomic environment and therefore are modeled separately only as a function of firm size.

[38] See Stuart A. Klugman, Harry H. Panjer, and Gordon E. Willmot, "Loss Models," *ASTIN Bulletin: The Journal of the IAA*, vol. 28 (May 1998): 163–66; and Paul Embrechts, Roger Kaufmann, and Gennady Samorodnitsky, "Ruin Theory Revisited: Stochastic Models for Operational Risk," ORIE Technical Reports (Ithaca, N.Y.: Cornell University Operations Research and Industrial Engineering, December 2002).

[39] See Patrick De Fontnouvelle, Virginia DeJesus-Rueff, John S. Jordan, and Eric S. Rosengren, "Capital and Risk: New Evidence on Implications of Large Operational Losses," *Journal of Money, Credit and Banking*, vol. 38, no. 7 (October 2006): 1819–46.

[40] The quarterly frequency of events is calculated as the cumulative number of events observed divided by the number of quarters for which operational-risk data are available for the relevant firm. In addition, the tail of frequency distribution is also informed by the historical industry loss frequency. The quarterly frequency is multiplied by nine to arrive at a nine-quarter frequency. Event-level severities are calculated as the ratio of losses from a given event to the assets of the firm at the time that it experienced the event.

Table 3.—*continued*

Variable	Description	Variable type	Source
Regression Model			
BBB corporate yield	ICE BBB 7-10 year bond yield index	Macroeconomic	FR supervisory scenarios
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
Market Volatility Index	Market Volatility Index (VIX) converted to quarterly frequency using the maximum close-of-day value in any quarter	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios

Note: Variables are listed alphabetically within variable type.

Loan Losses and Provisions on the Accrual Loan Portfolio

The Federal Reserve estimates accrual loan losses separately for different categories of loans, based on the type of obligor (e.g., consumer or commercial and industrial), collateral (e.g., residential real estate or commercial real estate), and loan structure (e.g., revolving credit lines).[41] These categories generally follow the classifications of the FR Y-9C, though some loss projections are made for more granular loan categories.

The Federal Reserve uses more than a dozen individual models to project losses on loans held in the accrual loan portfolio. The individual loan types modeled can broadly be divided into wholesale loans, such as C&I loans and CRE loans, and retail loans, including various types of residential mortgages, credit cards, student loans, auto loans, small-business loans, and other consumer loans.

For most loan types, losses in quarter t are estimated as the product of the projected PD, LGD, and EAD:

$$Loss(t) = PD(t) * LGD(t) * EAD(t). \tag{3}$$

The PD component measures the likelihood that a borrower enters default status during a given period t. The other two components capture the lender's loss on the loan if the borrower enters default. The LGD component measures the percent of the loan balance that the lender will not be able to recover after the borrower enters default, and the EAD component measures the total expected outstanding loan balance at the time of default.

Borrowers enter default if their recent payment history indicates that they will no longer make payments on a loan. The Federal Reserve's definition of default, for modeling purposes, may vary for different types of loans and may differ from general industry definitions or classifications. The Federal Reserve generally models PD as a function of loan characteristics and economic conditions. The Federal Reserve typically models LGD based on historical data, and modeling approaches vary for different types of loans. For certain loan types, the Federal Reserve models LGD as a function of borrower, collateral, or loan characteristics

41 The Federal Reserve models loans measured under fair-value accounting separately.

and the macroeconomic variables from the supervisory scenarios. For other loan types, the Federal Reserve assumes LGD is a fixed percentage of the loan balance for all loans in a category. Finally, the approach to modeling EAD varies by loan type and depends on whether the loan is a term loan or a line of credit.

For other loan categories, models capture the historical behavior of net charge-offs as a function of macroeconomic and financial market conditions and loan portfolio characteristics. The Federal Reserve then uses these models to project future charge-offs consistent with the evolution of macroeconomic conditions under the supervisory scenarios. To estimate projected losses, the projected net charge-off rate is applied to projected loan balances.

Wholesale Loans: Corporate Loans

Corporate loans consist of a number of different categories of loans, as defined by the FR Y-9C. These loans include graded C&I loans, agricultural loans, domestic farm loans, international farm loans, loans to foreign governments, loans for purchasing and carrying securities, other non-consumer loans, and other leases. The largest group of these loans is C&I loans, which are generally defined as loans to corporate or commercial borrowers with more than $1 million in committed balances that are graded using a firm's corporate loan rating process. The corporate loan model projects quarterly losses on these loans over the projection horizon of each stress test scenario.

The Federal Reserve estimates the model using historical data on corporate payment status and loan losses, loan characteristics, and economic conditions. The model projects these losses at the loan level in an expected-loss modeling framework, using data on firm-reported loan characteristics from the FR Y-14Q and economic conditions defined in the Federal Reserve's supervisory stress test scenarios.[42] Some of the key loan characteristics that affect projected losses include

- loan credit rating,
- the industry of the borrower,
- the country in which the borrower is domiciled, and
- whether or not the loan is secured.

The losses projected by the model for a given loan vary based on changes in the defined economic conditions over the projection horizon. Those include

- GDP growth,
- unemployment rate, and
- corporate bond spreads.

The PD component assumes that the probability that a loan defaults depends on macroeconomic factors such as the unemployment rate. The Federal Reserve defines corporate loans as in default when they are 90 days or more past due or in non-accrual status as of the reference date for the stress test. The model first calculates the loan's PD at the start of the projection

[42] The Federal Reserve does not require firms to report information about loans with less than $1 million in overall facility committed balances on schedule H.1 of the FR Y-14Q.

horizon and then projects it forward using the estimated relationship between historical changes in PD and changes in the macroeconomic environment.

The model calculates the initial PD, which is the PD at the start of the projection horizon, as the long-run average of expected default probabilities. Expected default probabilities are measures of the PD based on a structural model that links the value of a firm to credit risk. The initial PD for publicly traded borrowers reflects a borrower-specific expected default probability. The model bases the initial PD for other borrowers on the average expected default probability for the industry, country, and rating category group in which the borrower is classified. A borrower's industry and country category are directly observed in the firm-reported data, and the rating category is derived from the firm-reported internal credit rating for the borrower and a firm-reported table that maps the internal rating to a standardized rating scale.

The model projects initial PDs over the projection horizon using equations fitted to the historical relationship between changes in the expected default probabilities and changes in macroeconomic variables. The model estimates the equations separately by segments based on borrower industry, rating category, and country of borrower domicile in a regression framework.

The model specifies the change in PD for a given segment from period t-1 to t:

$$\Delta PD(t) = f\left(Z(t)\right), \tag{4}$$

where t represents time, $\Delta PD(t)$ represents the change in PD, and $Z(t)$ represents changes in one or more of the macroeconomic variables included in the supervisory scenarios.

These segment-level changes in PD estimated in equation (4) are applied to the loan-level initial PDs to calculate a loan-level path of PDs over the projection horizon.

The Federal Reserve uses firm-reported data on business lines and whether a loan is secured or unsecured to set the initial LGD for performing loans, which is at the start of the projection horizon. In cases in which the loan has already been identified as troubled (i.e., the firm has already set aside a reserve to cover the expected loss), the model bases initial LGD on the size of the reserve, and PD is set to 100 percent. For foreign loans, the model also adjusts initial LGDs based on the country in which the obligor is domiciled, capturing differences in collateral recovery rates across countries.

The model projects LGD for loan i at time t as a function of PD as follows:[43]

$$LGD(i,t) = f\left(LGD(i,t-1), PD(i,t), PD(i,t-1)\right), \tag{5}$$

where LGD represents the loss given default and PD represents the probability of default.

For closed-end loans, the EAD is the outstanding balance.[44] For standby letters of credit and trade finance credits, EADs are conservatively assumed to equal the total commitment since typically these types of credits are fully drawn when they enter default status. For lines of

[43] See Jon Frye and Michael Jacobs Jr., "Credit Loss and Systematic Loss Given Default," *Journal of Credit Risk*, vol. 8, no. 1 (March 2012): 109–40.

[44] The Federal Reserve collects information about a loan's outstanding balance in the item "Utilized Exposure Global" on the FR Y-14Q Schedule H.1.

credit and other revolving commitments, the EAD equals the outstanding balance plus a portion of the unfunded commitment (i.e., the difference between the committed exposure and outstanding balance), which reflects the amount that is likely to be drawn down by the borrower in the event of default. The Federal Reserve calibrates the amount that is likely to be drawn down to the historical drawdown experience for defaulted U.S. syndicated revolving lines of credit that are in the Shared National Credit (SNC) database.[45] The model sets the EAD for a line of credit or other revolving product as follows:

$$EAD(i) = OB(i) + LEQ * \left(C(i) - OB(i)\right), \tag{6}$$

where i represents the revolving product or line of credit, $EAD(i)$ represents the EAD, $OB(i)$ represents the line's outstanding balance at the start of the projection horizon, LEQ represents the calibrated drawdown rate, and $C(i)$ represents the line's committed balance at the start of the projection horizon.

Table 4. List of key variables in the corporate loan models and sources of variables

Variable	Description	Variable type	Source
PD model			
Country	The two-letter country code for the country in which the obligor is headquartered	Loan/Borrower characteristic	FR Y-14Q
Industry code	Numeric code that describes the primary business activity of the obligor	Loan/Borrower characteristic	FR Y-14Q
Obligor internal risk rating	The obligor rating grade from the reporting entity's internal risk rating system	Loan/Borrower characteristic	FR Y-14Q
BBB corporate yield	ICE BBB 7-10 year bond yield index	Macroeconomic	FR supervisory scenarios
Real GDP growth	Percent change in real gross domestic product, chained (2009) dollars, expressed at an annualized rate	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
LGD model			
Country	The two-letter country code for the country in which the obligor is headquartered	Loan/Borrower characteristic	FR Y-14Q
Credit facility type	The type of credit facility (potential types are defined in the FR Y-14Q H.1 corporate schedule)	Loan/Borrower characteristic	FR Y-14Q
Lien position	The type of lien (options include first-lien senior, second lien, senior unsecured, or contractually subordinated)	Loan/Borrower characteristic	FR Y-14Q
Line of business	The name of the internal line of business that originated the credit facility using the institution's own department descriptions	Loan/Borrower characteristic	FR Y-14Q
EAD model			
Committed exposure global	The current dollar amount that the obligor is legally allowed to borrow according to the credit agreement	Loan/Borrower characteristic	FR Y-14Q
Credit facility type	The type of credit facility (potential types are defined in the FR Y-14Q H.1 corporate schedule)	Loan/Borrower characteristic	FR Y-14Q
Utilized exposure global	The current dollar amount the obligor has drawn that has not been repaid, net of any charge-offs, ASC 310-30 (originally issued as SOP 0303) adjustments, or fair-value adjustments taken by the reporting institution, but gross of ASC 310-10 reserve amounts	Loan/Borrower characteristic	FR Y-14Q

Note: Variables are listed alphabetically within variable type.

[45] For additional information, see "Shared National Credit Program," Board of Governors of the Federal Reserve System, last modified March 9, 2017, https://www.federalreserve.gov/supervisionreg/snc.htm.

Wholesale Loans: Commercial Real Estate

CRE loans are defined as loans collateralized by domestic and international non-owner-occupied multifamily or nonfarm, nonresidential properties, and C&LD, as defined by the FR Y-9C.

The Federal Reserve estimates the model using historical data on CRE payment status and loan losses, loan characteristics, and economic conditions. The model projects these losses with an expected-loss modeling framework, using data on firm-reported loan characteristics for CRE loans with $1 million or more in committed balances from the FR Y-14Q and the economic conditions defined in the Federal Reserve's supervisory stress test scenarios.[46] Some of the key loan characteristics that affect projected losses include

- the loan type (i.e., income-producing or C&LD),
- the property type (e.g., multifamily, retail, hotel, office, and other),
- loan-to-value (LTV) ratio,
- loan size, and
- loan age and the proximity of the loan to maturity.

The losses projected by the model for a given loan vary based on changes in the defined economic conditions over the projection horizon. Those include

- corporate bond spreads,
- the unemployment rate,
- vacancy rates,
- house prices, and
- CRE prices.

The PD component assumes the probability that a loan defaults depends on loan characteristics and macroeconomic factors, such as the unemployment rate. The Federal Reserve defines CRE loans as in default when they are 90 days past due or other factors in the data (e.g., nonaccrual status or other evidence of weak credit quality when its maturity was last extended) indicate that the loans are significantly impaired. The PD component projects the probability that a loan transitions from current to default status. The model assumes that the loan, once in default, does not return to current status. The Federal Reserve models the probability that a loan defaults over a single quarter using a binomial logit regression model and estimates the model using data from the FR Y-14Q collection pooled with historical loan performance data on loans securitized in commercial mortgage-backed securities (CMBS).

The PD model is specified as

$$PD(i,t) = f\left(\lambda(i,t),\ X(i,t),\ Z(t)\right), \tag{7}$$

[46] The Federal Reserve does not require firms to report information about loans with less than $1 million in overall facility committed balances on schedule H.2 of the FR Y-14Q.

where i represents the loan, t represents time, $PD(i,t)$ represents the probability of default, $\lambda(i,t)$ represents a function of the age of loan i at time t, $X(i,t)$ represents loan and property characteristics, and $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios.

The LGD model calculates the loss conditional on a default, given the characteristics of the loan as well as macroeconomic variables at the time of default, including local commercial and local residential property prices and vacancy rates by property type. The Federal Reserve estimates the LGD for CRE loans using a Tobit model, based on industry-wide realized loss data on CRE loans. This approach accounts for the possibility that no loss may be experienced on the loan. The model sets LGD as follows:

$$LGD(i,t) = f\left(X(i), Z(t)\right), \tag{8}$$

where i represents the loan, t represents time, $X(i)$ represents loan and property characteristics at the loan origination date, and $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios.

The model estimates separate equations for income-producing loans and for C&LD loans. The loan-specific risk factors include factors such as origination LTV and loan size at origination. For income-producing loans, the model also includes controls for property type (i.e., apartment, hotel, industrial, office, and retail).

The PD and LGD models use projected unemployment rates, house prices, CRE vacancies, rents, and prices that are projected on the state, county, or metropolitan statistical area level.

The EAD model assumes EAD for CRE loans equals the total committed exposure amount, which is the outstanding balance of the loan plus any remaining undrawn committed amount at the start of the projection horizon.

Table 5. List of key variables in the CRE loan models and sources of variables

Variable	Description	Variable type	Source
PD Model			
Origination amount	The firm's total commitment as of the origination date	Loan/Borrower characteristic	FR Y-14Q
Property type	The reported property type of the loan	Loan/Borrower characteristic	FR Y-14Q
Value at origination	The reported value of the subject property at origination	Loan/Borrower characteristic	FR Y-14Q
BBB corporate yield	ICE BBB 7-10 year bond yield index	Macroeconomic	FR supervisory scenarios
Commercial Real Estate Price Index	Commercial Real Estate Price Index	Macroeconomic	FR supervisory scenarios
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios

(continued)

Table 5.—*continued*

Variable	Description	Variable type	Source
LGD Model			
Origination amount	The firm's total commitment as of the origination date	Loan/Borrower characteristic	FR Y-14Q
Property type	The reported property type of the loan	Loan/Borrower characteristic	FR Y-14Q
Value at origination	The reported value of the subject property at origination	Loan/Borrower characteristic	FR Y-14Q
Commercial Real Estate Price Index	Commercial Real Estate Price Index	Macroeconomic	FR supervisory scenarios
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
Commercial real estate vacancy rate	Vacancy rate of commercial real estate properties	Modeled input	Supervisory projections
EAD Model			
Committed exposure global	The current dollar amount the obligor is legally allowed to borrow according to the credit agreement	Loan/Borrower characteristic	FR Y-14Q

Note: Variables are listed alphabetically within variable type.

Retail Loans: Domestic First-Lien Residential Mortgages

Domestic first-lien mortgages are closed-end exposures that are secured by one- to four-family residential real estate located in the United States, as defined by the FR Y-9C.[47]

The Federal Reserve estimates the model using historical data on first-lien mortgage payment status and loan losses, loan characteristics, and economic conditions. The model projects losses on first-lien mortgages at the loan level in an expected-loss modeling framework, using data on firm-reported loan characteristics from the FR Y-14M and economic conditions defined in the Federal Reserve's supervisory stress test scenarios. Some of the key loan characteristics that affect projected losses include

- interest rate type (fixed or adjustable),
- LTV ratio, and
- borrower's credit score.

The losses projected by the model for a given loan vary based on changes in the defined economic conditions over the projection horizon. Those include

- house prices,
- the unemployment rate, and
- interest rates.

The PD component for first-lien residential mortgages projects the probability that a loan transitions to a different payment status (i.e., current, impaired, default, and paid off). The

[47] Loans are limited to first-lien, conventional home-purchase and refinance mortgages (excluding those insured by the Federal Housing Administration, guaranteed by the Department of Veterans Affairs, or backed by other government agencies) held in banks' portfolios, inclusive of loans that have been sold but subsequently returned to the seller.

Federal Reserve defines first-lien mortgages as in default when they are 180 days or more past due or when they have gone through foreclosure or have been prepaid with loss. First-lien mortgages are defined as current if they are no more than 89 days past due and are defined as impaired if they are between 90 and 179 days past due. The Federal Reserve uses separate PD models for fixed-rate mortgages and adjustable-rate mortgages. The Federal Reserve models the probability that a loan transitions from one payment status to another (e.g., from current to impaired or from impaired to default) over a single quarter using a regression framework.

The model is a system of five binomial logit models that generate a probability of default during a quarter of the projection horizon, conditional on the loan's payment status at the end of the prior quarter. Two of these models capture the transitions from a current state to other payment statuses: impaired or paid off. Three other models represent the transition from impaired status to other statuses. Impaired loans in the model may transition back to current, paid off, or default.[48] The model assumes default and paid-off loans to be terminal states, which means that loans cannot transition out of those states in the model.[49] Collectively, these models are a competing risks framework for default and prepayment and are specified as

$$\Pr\left(Tr\left(i,t+1\right) \mid S\left(i,t\right)\right) = f\left(X\left(i,t\right),\, Z\left(t\right)\right), \tag{9}$$

where i represents the loan, t represents time, $\Pr(Tr(i,\, t+1))$ represents the probability that the loan transitions to another status from period t to $t+1$, $S(i,t)$ represents the payment status in period t, $X(i,t)$ represents loan and borrower characteristics, and $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios.

The historical data used to estimate this model are industrywide, loan-level data on loans held in bank portfolios from many banks and mortgage loan originators. The PD model uses equation (9) to project a probability of default and prepayment for each loan in each quarter of the projection horizon.

The LGD models estimate loss at liquidation based on a number of factors, such as housing market conditions, the foreclosure legal environment, and loan characteristics.

The Federal Reserve projects the LGD for residential mortgages using two models. One model projects the length of time that elapses between default and liquidation (liquidation timeline model); the other model projects loss severity as a function of the projected liquidation timeline, as well as characteristics of the defaulted loan (loss severity model).[50]

The timeline model is estimated separately for borrowers in states in which foreclosure is conducted under judicial supervision and for non-judicial foreclosure states, using an accelerated failure time framework.

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[48] The binomial logit models in each subgroup approximate a multinomial logit model that models the competing risks of, for example, delinquency and paid off. To ensure that the transition probabilities to all states sum to 1, the Federal Reserve first models the conditional probabilities of each transition and then converts the conditional probabilities to unconditional probabilities when the binomial logit models are combined.

[49] The model captures the effects of loan modification and evolving modification practices in the probability that an impaired loan transitions back to current status.

[50] The Federal Reserve does not incorporate private mortgage insurance recovery into the LGD models.

For a loan that enters default, the timeline model is specified as

$$\ln\left(T(i)\right) = f\left(X(i,t), Z(t)\right), \tag{10}$$

where i represents the loan, t represents the time of default, $\ln(T(i))$ represents the log of the length of time between default and liquidation for defaulted loans i liquidated before the end of the sample period (uncensored loans) or the remaining time until the end of the sample period for those defaulted loans that have not yet been liquidated (censored loans), $X(i,t)$ represents a set of loan and borrower characteristics, and $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios.

The loss severity model estimates separate loss severity equations for prime, Alt-A, and subprime loans using a regression framework.[51] The loss severity model is specified in the following equation:

$$LGD(i,t) = f\left(X(i,t), T(i), Z\left(T(i)\right)\right), \tag{11}$$

where i represents the loan, t represents the time of default, $LGD(i,t)$ represents the loss severity rate of loan i that enters default at time t, $X(i,t)$ represents a set of loan and borrower characteristics, $T(i)$ represents the liquidation timeline for loan i, and $Z(T(i))$ represents one or more of the macroeconomic variables included in the supervisory scenarios at the time of liquidation.

Both the timeline models and loss severity models are estimated using loan-level data on loan balances, servicer advances, and losses from defaulted loans in commercially available datasets of agency and private-label mortgage-backed securities (MBS).

The Federal Reserve uses the projected time of liquidation to allocate estimated losses between credit losses on the defaulted loans and net losses arising from the eventual sale of the underlying property.[52] Finally, LGD includes unpaid accrued interest and an adjustment to reflect expected carrying costs on the loan that are not accounted for in PPNR projections (i.e., those carrying costs that would be incurred beyond the projection horizon).

The PD and LGD models use unemployment rates and house prices that are projected at the state and county levels.

The Federal Reserve assumes EAD to be the unpaid principal balance (UPB) at the start of the projection horizon.

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[51] The Federal Reserve classifies a loan as prime, Alt-A, or subprime depending on the borrower's credit score, LTV, and loan characteristics.

[52] Net losses arising from the eventual sale of the underlying property are OREO expenses, which are a component of PPNR.

Table 6. List of key variables in the first-lien mortgage models and sources of variables

Variable	Description	Variable type	Source
PD Model			
Credit score	Credit score of the borrower using a commercially available credit bureau score or equivalent	Loan/Borrower characteristic	FR Y-14M
Interest rate type	A variable to indicate the type of interest rate	Loan/Borrower characteristic	FR Y-14M
LTV	Loan-to-value ratio at origination	Loan/Borrower characteristic	FR Y-14M
Payment status	Payment status of the loan based on days past due	Loan/Borrower characteristic	FR Y-14M
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
Mortgage rate	Quarterly average of weekly series for the interest rate of a conventional, conforming, 30-year fixed-rate mortgage	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
3-month Treasury rate	Quarterly average of 3-month Treasury bill secondary market rate on a discount basis	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
LGD Model			
Credit score	Credit score of the borrower using a commercially available credit bureau score or equivalent	Loan/Borrower characteristic	FR Y-14M
LTV	Loan-to-value ratio at origination	Loan/Borrower characteristic	FR Y-14M
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
EAD Model			
Unpaid principal balance	The unpaid principal balance at the start of the projection horizon	Loan/Borrower characteristic	FR Y-14M

Note: Variables are listed alphabetically within variable type.

Retail Loans: Domestic Home Equity Loans and Home Equity Lines of Credit

Domestic home equity exposures include closed-end HELs and HELOCs, which are revolving, open-ended loans. HELs and HELOCs are secured by one- to four-family residential real estate located in the United States, as defined by the FR Y-9C.

The Federal Reserve estimates the model using historical data on home equity loans and lines of credit payment status, loan characteristics, and economic conditions. The model projects losses at the loan level in an expected-loss modeling framework using data on firm-reported loan characteristics from the FR Y-14M and economic conditions defined in the Federal Reserve's supervisory stress test scenarios. Some of the key loan and borrower characteristics that affect projected losses include

- combined LTV ratio,
- borrower's credit score, and
- utilization rate in the case of HELOCs.

The losses projected by the model for a given loan vary based on changes in the defined economic conditions over the projection horizon. Those include

- house prices,
- the unemployment rate, and
- interest rates.

The PD model for HELs and HELOCs projects the probability that a loan transitions to a different payment status (i.e., current, impaired, default, and paid off). The Federal Reserve defines home equity loans and lines of credit as in default when they are 180 days past due. The Federal Reserve also refers to accounts that reach 90 days past due as the intermediate "impaired state" in the analysis. Current and impaired loans may also transition to a paid-off state. The Federal Reserve estimates separate PD models for the two product types. At each point in time, each model uses a regression framework to estimate the probability that a loan transitions from one payment status to another status (e.g., from current to impaired or from impaired to default) over a single quarter.

The model is a system of five binomial logit equations that generates a probability of default during a quarter, conditional on the loan's payment status at the end of the prior quarter. Two of these equations capture the transitions from the current state to other payment statuses, which are either impaired or paid off. Three other equations represent the transition from impaired status to other statuses. Impaired loans in the model may transition to current, paid off, or default. The model assumes default and paid off to be terminal states and that loans in the model cannot transition out of those states. This model is specified as

$$\Pr\left(Tr\left(i,t+1\right) \mid S\left(i,t\right)\right) = f\left(X\left(i,t\right),\, Z\left(t\right)\right), \tag{12}$$

where i represents the loan, t represents time, $\Pr(Tr(i,\ t+1))$ represents the probability that the loan transitions to another status from period t to $t+1$, $S(i,t)$ represents the payment status in period t, $X(i,t)$ represents loan and borrower characteristics, and $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios.

Collectively, these models project a probability of default, conditional on product type, initial payment status, loan and borrower characteristics, and economic conditions over the projection horizon. The top panel of tables 7 and 8 contains a list of key variables that enter the PD models.

The HELOC PD model contains an additional feature to account for the fact that, for most lines of credit, the borrower may draw on the line for a fixed period, known as the "draw period," during which repayments of principal are not required. At the end of the draw period, the outstanding line balance either becomes immediately payable or converts to a fully amortizing loan. Borrowers holding these products after the draw period ends must make higher payments than were required during the draw period. The PD model assumes HELOCs that reach the end-of-draw period pay off and default at higher rates than HELOCs that are still in their draw period.

The LGD on a loan is the UPB on the HEL or HELOC at default minus net recovery after senior-lien payout. The net recovery after senior-lien payout is calculated as the proceeds from the liquidation sale net of foreclosure costs, less the balance of any senior liens and of unpaid accrued interest on this loan. Proceeds from liquidation is calculated by subtracting the senior-lien balance from the total recovery amount estimated by the first-lien LGD timeline and loss severity models.

The PD and LGD models use unemployment rates and house prices that are projected on the state and county levels.

The Federal Reserve assumes EAD for HELs to be the UPB of the loan at the start of the projection horizon. HELOCs that have been permanently closed or have reached the end-of-draw period are essentially closed-end loans. For these HELOCs, the Federal Reserve assumes EAD to equal the UPB at the start of the projection horizon. For all other HELOCs, the Federal Reserve sets EAD to the higher of the UPB at the start of the projection horizon and the original credit limit.

Table 7. List of key variables in the HEL exposure PD and EAD models and sources of variables

Variable	Description	Variable type	Source
PD Model			
Combined LTV	Combined loan-to-value ratio at origination	Loan/Borrower characteristic	FR Y-14M
Credit score	Credit score of the borrower using a commercially available credit bureau score or equivalent	Loan/Borrower characteristic	FR Y-14M
Loan age	Loan age in months	Loan/Borrower characteristic	FR Y-14M
Payment status	Payment status of the loan based on days past due	Loan/Borrower characteristic	FR Y-14M
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
3-month Treasury rate	Quarterly average of 3-month Treasury bill secondary market rate on a discount basis	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
LGD Model			
	See model description for first-lien mortgage		
EAD Model			
Unpaid principal balance	The unpaid principal balance at the start of the projection horizon	Loan/Borrower characteristic	FR Y-14M

Note: Variables are listed alphabetically within variable type.

Table 8. List of key variables in the HELOC exposure PD and EAD models and sources of variables

Variable	Description	Variable type	Source
PD Model			
Combined LTV	Combined loan-to-value ratio at origination	Loan/Borrower characteristic	FR Y-14M
Credit score	Credit score of the borrower using a commercially available credit bureau score or equivalent	Loan/Borrower characteristic	FR Y-14M
Payment status	Payment status of the loan based on days past due	Loan/Borrower characteristic	FR Y-14M

(continued)

Table 8.—*continued*

Variable	Description	Variable type	Source
Utilization rate	HELOC utilization (unpaid balance/original credit limit)	Loan/Borrower characteristic	FR Y-14M
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
Prime Rate	Quarterly average of monthly series	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
3-month Treasury rate	Quarterly average of 3-month Treasury bill secondary market rate on a discount basis	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
LGD Model			
	See model description for first-lien mortgage		
EAD Model			
Closed line status	Indicator of whether a line of credit is closed	Loan/Borrower characteristic	FR Y-14M
End-of-draw date	Last date the borrower can draw down a line of credit	Loan/Borrower characteristic	FR Y-14M
Original credit limit	The committed amount of the credit line at origination	Loan/Borrower characteristic	FR Y-14M
Unpaid principal balance	The unpaid principal balance at the start of the projection horizon	Loan/Borrower characteristic	FR Y-14M

Note: Variables are listed alphabetically within variable type.

Retail Loans: Domestic Credit Cards

Domestic credit cards include general purpose, private-label, and charge cards, as defined by the FR Y-9C.[53]

The model projects losses at the account level in an expected-loss modeling framework, using data on firm-reported characteristics from the FR Y-14M and economic conditions defined in the Federal Reserve's supervisory stress test scenarios.[54] Some of the key characteristics that affect projected losses include

- lending type (i.e., bank card or charge card),
- account holder's credit score,
- credit line (i.e., limit) of the account, and
- account utilization rate factor.

The losses projected by the model for a given account vary based on changes in the defined economic conditions over the projection horizon. The key macroeconomic variable that enters the model is the unemployment rate.

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53 The Federal Reserve includes credit card loans extended to individuals in the retail credit cards model. Credit card loans extended to businesses and corporations are modeled separately.

54 These losses are adjusted to reflect agreements with private entities to share a portion of both revenues and losses generated by a specific credit card portfolio. See Appendix A for additional details.

The PD model for credit cards estimates the probability that an account transitions to default status, given the characteristics of the account and borrower as well as macroeconomic conditions. The Federal Reserve defines credit card accounts as in default when they are 120 days or more past due, in bankruptcy, or charged off. When an account defaults, it is assumed to close and cannot return to current status in the model.

Because the relationship between the PD and its determinants can vary with the payment status of the account, the Federal Reserve estimates separate transition models for current and active accounts, current and inactive accounts, and delinquent accounts.[55] In addition, because this relationship can also vary by lending type and time horizon, the Federal Reserve uses separate models by lending type and over the short-, medium-, and long-term horizons. These transition models correspond to default in the first quarter, the second and third quarters, and the fourth through ninth quarters of the horizon, respectively. The historical data used to estimate this model are industrywide, account-level data. The probability that an account defaults in a quarter is modeled in a binomial logit regression model:

$$PD(i,t) = f\left(X(i,t), Z(t)\right), \tag{13}$$

where i represents the account, t represents time, $PD(i,t)$ represents the probability of default, $X(i,t)$ represents account and borrower characteristics, and $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios.

The PD model uses unemployment rates that are projected at the state level.

The LGD model assumes that LGD for credit cards is a fixed percentage of EAD. This percentage is calculated separately for bank cards and charge cards based on historical industry data of gross charge-offs and recoveries during the most recent economic downturn.

The EAD for credit cards is equal to the sum of the amount outstanding on the account (i.e., UPB) and the estimated amount of the credit line that is likely to be drawn down by the borrower between the beginning of the projection horizon and the time of default. The model calculates EAD for an account that defaults at a specific time as

$$EAD(i,t) = UPB(i) + LLEQ(i,t) * C(i), \tag{14}$$

where i represents the account, t represents time, $EAD(i,t)$ represents the EAD, $UPB(i)$ represents the reported unpaid balance of account i at the start of the projection horizon, $C(i)$ represents the reported credit line of account i at the start of the projection horizon, and $LLEQ(i,t)$ represents a utilization factor.

[55] The Federal Reserve defines credit card accounts as active and current if they have had activity in the past 12 months and are no more than 29 days past due, delinquent if they are between 30 and 119 days past due, and inactive if they have had no activity in the past 12 months and are no more than 29 days past due.

As shown below, $LLEQ(i,t)$ is estimated as a function of account and borrower characteristics:

$$LLEQ(i,t) = f\left(X(i,t)\right). \tag{15}$$

Because the relationship of this factor to account and borrower characteristics can vary with the payment status of the account and time to default, the Federal Reserve uses separate models to estimate the drawdown amount for current and delinquent accounts and for accounts with short-, medium-, and long-term transitions to default. For accounts that are current, the Federal Reserve estimates separate models for segments with credit lines of different sizes. The Federal Reserve adjusts estimated EAD to exclude delinquent interest and fees.[56]

Table 9. List of key variables in the credit card models and sources of variables

Variable	Description	Variable type	Source
PD Model			
Credit line	The dollar amount the account holder is legally allowed to borrow according to the credit agreement	Account/Borrower characteristic	FR Y-14M
Credit score	Credit score of the account holder using a commercially available credit bureau score or equivalent	Account/Borrower characteristic	FR Y-14M
Cycle ending balance	The total outstanding balance for the account at the end of the month's cycle	Account/Borrower characteristic	FR Y-14M
Lending type	An indicator variable for consumer and non-consumer bank and charge cards	Account/Borrower characteristic	FR Y-14M
Payment status	Payment status of the loan based on days past due	Account/Borrower characteristic	FR Y-14M
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
LGD Model			
Gross charge-offs	Gross charge-offs as a percentage of card balances	Portfolio characteristics	FR Y-9C
Gross recoveries	Gross recoveries as a percentage of card balances	Portfolio characteristics	FR Y-9C
EAD Model			
Credit line	The dollar amount the account holder is legally allowed to borrow according to the credit agreement	Account/Borrower characteristic	FR Y-14M
Cycle ending balance	The total outstanding balance for the account at the end of the month's cycle	Account/Borrower characteristic	FR Y-14M
Lending type	An indicator variable for consumer and non-consumer bank and charge cards	Account/Borrower characteristic	FR Y-14M
Payment status	Payment status of the loan based on days past due	Account/Borrower characteristic	FR Y-14M
Loan-over-line-equivalent concept (LLEQ)	Account utilization factor, estimated as a function of account and borrower characteristics	Modeled input	Supervisory projections

Note: Variables are listed alphabetically within variable type.

Retail Loans: Domestic Auto

Domestic auto loans are consumer loans that are extended for the purpose of purchasing new and used automobiles and light motor vehicles, as defined by the FR Y-9C.

56 Delinquent interest and fees are often reversed upon default and reflected in reduced PPNR rather than as credit losses.

The Federal Reserve estimates the model using historical data on auto payment status and loan losses, loan characteristics, and economic conditions. The model projects losses at the portfolio-segment level with an expected-loss framework, using data on firm-reported loan characteristics from the FR Y-14Q and economic conditions defined in the Federal Reserve's supervisory stress test scenarios.[57] Some of the key loan and borrower characteristics that affect projected losses include

- product type (new or used vehicle),
- loan age,
- LTV ratio, and
- borrower's credit score.

The losses projected by the model vary based on changes in the defined economic conditions over the projection horizon. Those include

- the unemployment rate and
- house prices.

The PD model estimates the probability that a loan transitions its status from either a current or delinquent state to default status, given the characteristics of the loan and borrower and macroeconomic variables, including house prices and the unemployment rate. The Federal Reserve defines auto loans as in default if the vehicle is in repossession or if the loan is 120 days or more past due, in bankruptcy, or charged off. The model estimates the probability that a loan defaults in a quarter using historical loan-level data from a major credit bureau. Because the relationship between the PD and its determinants can vary with the payment status of the loan, the Federal Reserve estimates two separate transition models for loans that are current and for those that are delinquent.[58] The probability that a loan defaults is modeled in a binomial logit regression framework:

$$PD(i,t) = f\left(X(i,t),\ Z(t)\right), \tag{16}$$

where i represents the loan, t represents time, $PD(i,t)$ represents the probability of default, $X(i,t)$ represents loan and borrower characteristics, such as credit score and loan age, and $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios. The model projects PDs by applying the coefficient estimates from model (16) to specific loan segments from the FR Y-14Q regulatory report.

The Federal Reserve models the LGD for auto loans as a function of loan as well as borrower characteristics and macroeconomic variables. The historical data used to estimate this model are pooled, segment-level data provided by the firms in the FR Y-14Q report. The model estimates the LGD for defaulted loans within a segment using the following linear regression model:

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[57] The Federal Reserve specifies loan segments in the FR Y-14Q Schedule, Section A.2 – US Auto Loan.

[58] The Federal Reserve defines auto loans as current if they are no more than 29 days past due and as delinquent if they are between 30 and 119 days past due (unless subject to bankruptcy or repossession).

$$LGD(k,t) = f\left(X(k), Z(t)\right), \tag{17}$$

where k represents the segment, t represents time, $LGD(k,t)$ represents the loss given default, $X(k)$ represents characteristics of the segment k, such as product type, LTV, and loan segment age, and $Z(t)$ represents one or more of the macroeconomic variables included in the supervisory scenarios. The model then projects LGD by applying coefficient estimates from equation (17) to segment-level data from the FR Y-14Q.

The LGD model uses projected values of a national used car price index in addition to unemployment rates and house prices that are projected on the state level.

The Federal Reserve bases the EAD for auto loans on the pattern of amortization of loans that ultimately defaulted in the data provided by a major credit bureau, as reflected in the following equation:

$$EAD(k,t) = UPB(k) * PR(k,t), \tag{18}$$

where k represents the loan age segment, t represents time, $EAD(k,t)$ represents the EAD, $UPB(k)$ represents the unpaid principal balance for loan segment k, and $PR(k,t)$ represents a paydown ratio for loan segment k at period t. $PR(k,t)$ is estimated as a function of loan characteristics.

Table 10. List of key variables in the auto loan models and sources of variables

Variable	Description	Variable type	Source
PD model			
Credit score	Credit score of the borrower using a commercially available credit bureau score or equivalent	Loan/Borrower characteristic	FR Y-14Q
Loan age	Loan age in years	Loan/Borrower characteristic	FR Y-14Q
Payment status	Payment status of the loan based on days past due	Loan/Borrower characteristic	FR Y-14Q
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
LGD Model			
Loan age	Loan age in years	Loan/Borrower characteristic	FR Y-14Q
LTV	Loan-to-value ratio at origination	Loan/Borrower characteristic	FR Y-14Q
Product type	An indicator variable reflecting a new or used vehicle	Loan/Borrower characteristic	FR Y-14Q
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios

(continued)

Table 10.—*continued*

Variable	Description	Variable type	Source
EAD Model			
Unpaid principal balance	The unpaid principal balance at the start of the projection horizon	Loan/Borrower characteristic	FR Y-14Q
Paydown ratio	The historical average of balance paydowns until default (as a percentage of balances on the effective date of the stress test)	Modeled input	Supervisory projections

Note: Variables are listed alphabetically within variable type.

Retail Loans: Other Retail Loans

The other retail loans category includes the small-business loan portfolio, other consumer loan portfolio, student loan portfolio, business and corporate credit card portfolio, international other consumer loan portfolio, international bank and charge card loan portfolio, international first mortgage portfolio, international home equity loan portfolio, international small-business loan portfolio, and international small-business and corporate credit card portfolio. The Federal Reserve generally defines these categories based on the FR Y-9C classifications.

The Federal Reserve estimates these models using historical data on loan payment status, loan losses, loan characteristics, and economic conditions. Net charge-offs are projected at the segment level using the estimated models, firm-reported loan characteristics from the FR Y-14Q, and economic conditions defined in the supervisory stress test scenarios. The models calculate losses by applying projected net charge-off rates to balances projected by the Federal Reserve. Key portfolio characteristics that affect projected losses include

- product type within a portfolio,
- payment status,
- borrower's credit score, and
- LTV ratios for certain products.

The losses projected by each model for a given portfolio vary based on changes in the defined economic conditions over the projection horizon. Those include variables such as

- unemployment rate,
- real disposable income growth, and
- domestic and international real GDP growth.

The Federal Reserve models a net charge-off rate for each portfolio using industry-wide, monthly data at the segment level. For most portfolios, the Federal Reserve collects these data at the segment level in the FR Y-14Q Retail schedule, where segments are defined based on loan characteristics.[59] The Federal Reserve defines other retail loans as in default when they are 90 days or more past due for domestic and international other consumer loans

[59] Business and corporate credit card portfolio data, previously collected in the FR Y-14Q Retail schedule, are now collected at the loan level on the FR Y-14M Credit Card schedule and are subsequently aggregated to the segment level.

and 120 days or more past due for student loans, small-business loans, corporate card loans, and international retail portfolios.

The models project the net charge-off rate using a system of equations that also generates projections of the delinquency rate and default rate:

$$Payment\,status(b,k,t) = f(X(b,k,t), Z(t)), \tag{19}$$

where b represents the firm, k represents a segment of loans within the portfolio, t represents time, $X(b,k,t)$ includes the payment status in the prior period and risk segment indicators, and $Z(t)$ represents macroeconomic variables in different lags. The Federal Reserve models delinquency, default, and net charge-off rates using an autoregressive specification as a function of its own value in the previous period t-1 and the rate in the previous performance state to capture the transition from one state to the other. The specification also includes risk-segment-specific effects and macroeconomic variables.[60] The models use projected values of international GDP growth for certain geographic areas. The models estimate the parameters using a weighted least squares regression and include seasonal factors for select portfolios.

The Federal Reserve models each of the 10 loan portfolios separately. By including lags of the delinquency rates and default rates in the default and net charge-off models, respectively, the models implicitly capture roll-rate dynamics.[61]

The models project charge-off rates by applying the estimated system of equations to each segment of the firm's loan portfolio, as of the effective date of the stress test. The portfolio-level charge-off rate equals the dollar-weighted average of the projected segment-level charge-off rates.[62]

Table 11. List of key variables in other retail models and sources of variables

Variable	Description	Variable type	Source
Domestic and international			
Credit score	Credit score of the borrower using a commercially available credit bureau score or equivalent	Loan/Borrower characteristic	FR Y-14Q, FR Y-14M
LTV	Loan-to-value ratio at origination	Loan/Borrower characteristic	FR Y-14Q, FR Y-14M
Net charge-offs	The dollar amount of write-downs, net of any recoveries in the reporting segment and month	Loan/Borrower characteristic	FR Y-14Q, FR Y-14M
Payment status	Payment status of the loan based on days past due	Loan/Borrower characteristic	FR Y-14Q, FR Y-14M
Product type	Segments of the portfolio based on various features of the credit	Loan/Borrower characteristic	FR Y-14Q, FR Y-14M

(continued)

[60] The risk segments are combinations of borrower's credit score, product type, borrower geographic location, and other characteristics that describe different loan types.

[61] *Roll-rate dynamics* refers to the transition of delinquent loans to defaulted loans in one period and the transition of defaulted loans to net charge-offs in the next period.

[62] The models base the dollar weights used on the distribution reported during the previous observation period. This method assumes that the distribution of loans across risk segments, other than delinquency status segments, remains constant over the projection period.

Table 11.—*continued*

Variable	Description	Variable type	Source
Domestic			
Real disposable income growth	Percent change in disposable personal income (current dollars) divided by the price index for personal consumption expenditures, expressed at an annualized rate	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
International			
Developing Asia real GDP growth	Percent change in real gross domestic product at an annualized rate	Macroeconomic	FR supervisory scenarios
Euro area real GDP growth	Percent change in real gross domestic product at an annualized rate	Macroeconomic	FR supervisory scenarios
Real GDP growth	Percent change in real gross domestic product, chained (2009) dollars, expressed at an annualized rate	Macroeconomic	FR supervisory scenarios

Note: Variables are listed alphabetically within variable type.

Adjustments to Losses and Calculation of Loan-Loss Provisions for the Accrual Loan Portfolio

Loss models focus on losses arising from loans that are in the accrual loan portfolio as of the effective date of the stress test, but loss projections also incorporate losses on loans originated after the projection horizon begins. These incremental loan balances are calculated based on projected loan balances over the projection horizon. New balances are assumed to have the same risk characteristics as those of the loan portfolio on the effective date of the stress test, with the exception of loan age in the retail and CRE portfolios, where seasoning is incorporated.

New loans are assumed to be current, and firms are assumed not to originate types of loans that are no longer permitted under various regulations. Loss projections generated by the models are adjusted to take account of purchase accounting treatment, which recognizes discounts on impaired loans acquired during mergers and any other write-downs already taken on loans held in the accrual loan portfolio. This latter adjustment ensures that losses related to these loans are not double-counted in supervisory projections.

Losses on the accrual loan portfolio enter net income through provisions for loan and lease losses. Provisions for loan and lease losses for each quarter equal projected loan losses for the quarter plus the change in the allowance needed to cover the subsequent four quarters of expected loan losses, taking into account the allowance established at the start of the projection horizon.

The Federal Reserve generally assumes the appropriate level of the allowance in the supervisory calculations to be the amount needed to cover projected loan losses over the next four quarters.[63] The supervisory calculation of the allowance is based on projected losses under the severely adverse scenario and may differ from a firm's established allowance at the beginning of the projection horizon, which is based on the firm's estimate of incurred losses on the effective date of the stress test. Any difference between these two measures of the allowance is

[63] For loan types modeled in a charge-off framework, the Federal Reserve adjusts the appropriate level of the allowance to reflect the difference in timing between the recognition of expected losses and that of charge-offs.

linearly smoothed into the provisions projection over the nine quarters of the projection horizon. Thus, the calculation takes into account the allowance established by the firm. Because projected loan losses include off-balance sheet commitments, the supervisory calculation of provisions also accounts for the firm's allowance for credit losses on off-balance sheet exposures on the effective date of the stress test.

Table 12. List of key variables in the loan-loss provisions calculation for the accrual loan portfolio

Variable	Description	Variable type	Source
Allowance for credit losses on off-balance sheet credit exposures	Dollar amount of allowance that is appropriate to cover estimated credit losses associated with off-balance sheet credit instruments	Firm characteristic	FR Y-9C
Allowance for loan and lease losses	Dollar amount of allowance for loan and lease losses that is appropriate to cover estimated credit losses associated with loan and lease portfolios	Firm characteristic	FR Y-9C
Loan losses	Losses on wholesale and retail loans in the accrual portfolios as estimated by supervisory models	Modeled input	Supervisory projections

Note: Variables are listed alphabetically within variable type.

Other Losses

FVO/HFS Loans

FVO/HFS loans are treated differently from accrual loans under the accounting standards. FVO loans are valued as mark-to-market assets, while HFS loans are carried at the lower of cost or market value. As a result, FVO/HFS loans can experience gains or losses when their fair values change in response to changes in macroeconomic and financial market conditions. The Federal Reserve recognizes gains and losses related to FVO/HFS loans in earnings on the income statement at the time of the revaluation.

Fair value gains and losses are defined as changes in the fair value of the loan or commitment. The Federal Reserve uses different models to estimate gains and losses on FVO/HFS wholesale loans and FVO/HFS retail loans. Generally, these models project gains and losses over the nine-quarter projection horizon, net of hedges, by applying the scenario-specific interest rate and credit spread shocks to loan yields.

FVO/HFS Wholesale Loans

The Federal Reserve projects gains and losses on FVO/HFS wholesale loans and commitments by revaluing each loan or commitment each quarter and computing quarterly changes in fair value in each quarter of the projection horizon. The key loan characteristics that affect projected losses include

- loan rating,
- interest rate of the loan, and
- maturity date.

The key macroeconomic variables that enter the model are

- credit spreads and
- interest rates.

The Federal Reserve models fair value using a standard bond pricing formula for fixed-rate loans and a linear approximation for floating-rate loans. For fixed-rate loans, the bond pricing formula discounts future cash flows using a discount yield that depends on loan rating and maturity. To project fair value, the model assumes that the discount yield can change due to changes in both loan-specific characteristics and macroeconomic variables.

The model infers a starting point discount yield for a loan at the start of the projection horizon using the firm-reported fair value.

The discount yield in a projection quarter can be written as

$$y\left(i,t,r\left(0\right),r\left(t\right)\right)=y\left(i,0\right)+\Delta s\left(i,t,r\left(0\right),r\left(t\right)\right)+\Delta ir\left(i,t\right), \tag{20}$$

where i represents the loan, t represents time, $r(0)$ represents the rating at the start of the projection horizon, $r(t)$ represents the rating in quarter t, $y\ (i,t,r(0),r(t))$ represents the discounted yield, $y(i,0)$ represents the yield at the start of the projection horizon, $\Delta s(i,t,r(0),r(t))$ represents the rating- and maturity-specific projected change in the credit spread since the start of the projection horizon, and $\Delta ir(i,t)$ represents the change in the interest rate since the start of the projection horizon.

The Federal Reserve proxies spreads on FVO/HFS wholesale loans by those on a U.S. high-yield security index and by projected spreads calibrated to the BBB yield in the macroeconomic scenario. The Federal Reserve projects movements in spreads over the projection horizon based on their historical relationships with macroeconomic and financial variables. The model projects loan-specific discount yields for all possible rating changes in all projection periods. The model then uses the projected discount yields in equation (20) and the bond pricing formula, or linear approximation, to compute rating-specific fair values. The projected fair value is the expected fair value, over all possible ratings changes, where probabilities of rating changes are taken from a historical empirical ratings transition matrix.[64]

FVO/HFS Retail Loans

FVO/HFS retail loans include first- and second-lien mortgages, student loans, credit cards, and auto loans.[65] The Federal Reserve calculates gains and losses on FVO/HFS retail loans over the nine quarters of the projection horizon using a duration-based approach. This approach uses total loan balances as reported on the FR Y-14Q, estimates of portfolio-weighted duration, and quarterly changes in stressed spreads from the supervisory stress test scenarios. Estimates are calculated separately by vintage and loan type.

Gains and losses on FVO/HFS retail loans of a particular loan type and vintage in a projection quarter are specified as follows:

$$Loss\left(j,v,t\right)=CV\left(j,v,0\right)*D\left(j,v\right)*\Delta s\left(j,t\right), \tag{21}$$

where j represents loan type, v represents vintage, t represents the projection quarter, $Loss(j,v,t)$ represents the gain or loss on the FVO/HFS retail loan, $CV(j,v,0)$ represents the

64 For loans that are projected to transition into default, a loss given default assumption is applied to committed exposures.

65 The Federal Reserve assumes zero losses for residential mortgages under forward contract with GSEs.

carrying value as defined in Schedule J of the FR Y-14Q, $D(j,v)$ represents a measure of duration, and $\Delta s(j,t)$ represents the change in loan spreads since the start of the projection horizon. The Federal Reserve projects spreads on highly-rated asset-backed security indexes and uses them as a proxy for spreads on FVO/HFS retail loans. Movements in spreads over the projection horizon are based on their historical relationships with macroeconomic variables.

FVO Loan Hedges

The Federal Reserve calculates the quarterly profit and loss (P&L) on FVO loan hedges by combining a set of scenario-specific risk-factor projections and factor sensitivities submitted by firms. The Federal Reserve nets aggregate hedge gains and losses for each firm against projected gains and losses on wholesale and retail exposures to estimate the firm's final P&L projections.

Table 13. List of key variables in the FVO/HFS models and sources of variables

Variable	Description	Variable type	Source
Wholesale sub-model			
Committed exposure	The dollar amount the obligor is contractually allowed to borrow according to the credit agreement or commitment letter, regardless of whether the commitment is legally binding	Loan characteristic	FR Y-14Q
Fair-value adjustment committed exposure	The dollar amount adjustment (positive or negative) from the committed exposure par balance for loans held for sale or under a fair-value option. The fair-value adjustment represents the fair value of the entire credit facility minus the dollar amount the obligor is contractually allowed to borrow according to the credit agreement	Loan characteristic	FR Y-14Q
Loan interest rate	Interest rate of the loan	Loan characteristic	FR Y-14Q
Maturity date	The maturity date is the last date on which the funds must be repaid, inclusive of extension options and according to the most recent terms of the credit agreement	Loan characteristic	FR Y-14Q
Obligor internal risk rating	The firm's internal ratings of its obligors	Loan characteristic	FR Y-14Q
BBB corporate yield	ICE BBB 7-10 year bond yield index	Macroeconomic	FR supervisory scenarios
Rating transition matrix	Historical empirical credit transition matrices	Macroeconomic	Commercially available data
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
3-month Treasury rate	Quarterly average of 3-month Treasury bill secondary market rate on a discount basis	Macroeconomic	FR supervisory scenarios
Retail sub-model			
BBB corporate yield	ICE BBB 7-10 year bond yield index	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
3-month Treasury rate	Quarterly average of 3-month Treasury bill secondary market rate on a discount basis	Macroeconomic	FR supervisory scenarios
Carrying value	Carrying value of the loan portfolio following the definition in Schedule J of the FR Y-14	Portfolio characteristic	FR Y-14Q

(continued)

Table 13.—*continued*

Variable	Description	Variable type	Source
Hedges sub-model			
Factor sensitivities	P&L slides (grids) that map hypothetical risk-factor shocks to net gains or losses on hedge positions	Hedge table	FR Y-14Q, FVO hedge collection
BBB corporate yield	ICE BBB 7-10 year bond yield index	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios

Note: Variables are listed alphabetically within variable type.

AFS and HTM Securities

Losses on securities[66] can arise from two different sources. For AFS securities, fair value reflected on the balance sheet may change due to changes in economic or financial conditions. These gains or losses are reported as OCI and are included in CET1 for firms subject to the advanced approaches. In addition, both AFS and HTM securities may be at risk of credit losses.[67]

The models project credit losses and OCI for each applicable security and aggregate these losses up to the firm level in three steps. First, the models project the fair value of each security over the nine-quarter projection horizon, conditional on the supervisory stress test scenarios. Second, the models estimate security-level credit losses as a function of book value and the projected change in fair value. Finally, the models calculate OCI from AFS securities using projected changes in fair value, accounting for any projected credit losses.

All securities loss models are estimated using security-level information from the FR Y-14Q and economic conditions in order to project credit losses and OCI from AFS securities. Some of the key security characteristics that affect projected losses include

- maturity date,
- security type,
- market values and amortized costs of the securities, and
- measures of duration.

The losses projected by the model for a given security vary based on changes in economic conditions over the nine quarters of the projection horizon. Those include

- interest rates,
- stock market returns and volatility, and
- corporate bond spreads.

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66 The Federal Reserve does not include securities held by a firm in its trading book in the AFS/HTM portfolio and projects their losses separately in the Trading and Private Equity models. See "Trading and Private Equity" below.

67 For firms that have adopted ASU 2016-13 in 2020, expected credit losses relating to AFS and HTM debt securities are recorded through the allowance for credit losses.

Fair Value of Securities

The Federal Reserve projects the fair value of fixed-income securities (i.e., bonds) over the nine-quarter projection horizon using one of three methods: a simple present-value calculation, a full revaluation based on a security-specific discounted cash flow model, or a duration-based approach.

The fair value of U.S. Treasuries is projected as a present-value calculation using a formula that defines the security price as the present value of future expected cash flows, discounted by security-specific discount rates. This formula uses yields specified in the macroeconomic scenarios, which are the paths for 3-month, 5-year, and 10-year U.S. Treasury yields. The Federal Reserve uses a term structure model to interpolate or extrapolate yields for other maturity points.[68]

Full revaluation of agency MBS is projected using a discounted-cash-flow simulation model, which is an industry-standard modeling technique for agency MBS. The main drivers of change in the fair values of agency MBS are interest rates used for discounting the expected cash flows, house prices, the unemployment rate, and projected movements in a MBS option-adjusted spread (OAS) index. The Federal Reserve projects movements in spreads over the projection horizon based on their historical relationships with macroeconomic and financial variables.

The Federal Reserve projects the fair value for fixed-income securities other than U.S. Treasuries and agency MBS using a duration-based approximation. The duration-based approximation projects the quarterly price path based on a first-order approximation of the relationship between the security price and its yield, taking into account security-specific information.

The model projects the fair value for a security with a specific maturity as

$$\%\Delta FV(i,t) = -\left(D(i,spread) * \Delta OAS(i,t) + D(i,Rate) * \Delta RF(T,t)\right), \tag{22}$$

where i represents a security, t represents time, T represents maturity, $\%\Delta FV(i,t)$ represents the percent change in fair value, $D(i,spread)$ and $D(i,Rate)$ represent the effective spread and rate durations for security i, $\Delta OAS(i,t)$ represents the modeled expected change in the OAS of security i in quarter t, and $\Delta RF(T,t)$ represents the change in yield on a U.S. Treasury with maturity T in quarter t. The Federal Reserve projects these expected changes in OAS using separate regression models for each asset class.

For each asset class, the Federal Reserve projects the OAS using regression models that relate historical values of the spreads to key macroeconomic and financial characteristics, such as the BBB corporate spread and the U.S. Dow Jones Total Stock Market Index return. OAS is projected using separate models for corporate bonds, sovereign bonds, and all other fixed-income securities. The sovereign bond OAS is projected based on high-percentile historical movements in sovereign bond spreads. This percentile is related to the frequency of severe recessions.

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[68] See Jens H. E. Christensen and Jose A. Lopez, "Common Risk Factors in the US Treasury and Corporate Bond Markets: An Arbitrage-Free Dynamic Nelson-Siegel Modeling Approach," unpublished paper, Federal Reserve Bank of San Francisco, October 2012, https://www.frbsf.org/economic-research/files/Treasury-risk-AFDNS.pdf.

For equity securities, the Federal Reserve projects fair value using the expected return on a broad market portfolio.

For all asset classes, fair value projections assume that duration and remaining life remain constant.

Credit Losses on AFS/HTM Securities

In the supervisory stress test, the Federal Reserve assumes that U.S. Treasuries, U.S. government agency obligations, U.S. government agency or government-sponsored enterprise MBS, Federal Family Education Loan Program student loan asset-backed securities, and pre-refunded municipal bonds are not subject to credit losses.

For all other debt securities, the model used to project credit losses is estimated using historical data, which assumes that security-level credit losses depend on two risk factors: a term that measures the deviation of the fair value of the security from its book value, and a term that measures the recent changes in fair value. Specifically, the model takes the form:

$$\frac{CL(i,t)}{BV(i,t-1)} = g\left(\underbrace{\frac{FV(i,t-1)}{BV(i,t-1)}}_{Market-to-book}, \underbrace{\frac{(FV(i,t)) - FV(i,t-1)}{FV(i,t-1)}}_{Return}\right), \tag{23}$$

where i represents the security, t represents the year, $CL(i,t)$ represents the credit loss taken on the security holding i in year t, $BV(i,t\text{-}1)$ represents the amortized cost of the holding i at the end of year $t\text{-}1$, $FV(i,t)$ represents the fair market value of the holding i at the end of year t, and g represents a function estimated using fractional logit.[69] The Federal Reserve estimates the model with historical data on securities' amortized costs, fair values, and credit write-downs obtained from the FR Y-14Q as well as from additional data from filings on the securities holdings of U.S. life insurance companies.

The Federal Reserve estimates model parameters separately for direct debt obligations and securitized obligations. The model specification accounts for different asset classes within each group using asset-class indicator variables. Securitized obligations include MBS, asset-backed securities, CLOs, and CDOs. Direct debt obligations are issued by a single issuer with recourse and include asset classes such as municipal, corporate, and sovereign debt securities.

The model computes credit losses using projections from the fair-value models and iterating on equation (23) at an annual horizon. In the first year of the horizon, the model uses the book value and market-to-book ratio for each security as of the effective date of the stress test. Annual projected credit loss is distributed equally across quarters.

Calculation of OCI

Firms subject to the advanced approaches are required to include AOCI in regulatory capital.

[69] Prior to the adoption of ASU 2016-13 (see note 14), securities credit losses were realized through other-than-temporary impairment (OTTI). For firms under the CECL standard, credit losses are measured as an allowance rather than as a write-down.

OCI for a given AFS security in a certain quarter of the projection horizon is calculated as the difference between the change in fair value for the holding in that quarter and the change in the amortized cost of the holding in that quarter. Final projections adjust for any credit loss taken and take into account applicable interest rate hedges on securities, but do not account for periodic amortization or accretion.

The Federal Reserve assumes that balances at risk of credit loss do not decrease. After a security experiences a credit loss, the Federal Reserve assumes the difference between its original value and its post-credit loss value to be invested in securities with the same risk characteristics. New balances of securities due to projected balance growth are assumed to be in short-term, riskless assets, and no credit loss or OCI is projected on those balances.

Table 14. List of key variables in the securities models and sources of variables

Variable	Description	Variable type	Source
Fair-value models			
BBB corporate yield	ICE BBB 7-10 year bond yield index	Macroeconomic	FR supervisory scenarios
Dow Jones Total Stock Market Index	End-of-quarter value	Macroeconomic	FR supervisory scenarios
House Price Index	Price index for owner-occupied real estate	Macroeconomic	FR supervisory scenarios
Market Volatility Index	Market Volatility Index (VIX) converted to quarterly frequency using the maximum close-of-day value in any quarter	Macroeconomic	FR supervisory scenarios
10-year Treasury yield	Quarterly average of the yield on 10-year U.S. Treasury bonds	Macroeconomic	FR supervisory scenarios
Unemployment rate	Quarterly average of seasonally-adjusted monthly data for the unemployment rate of the civilian, noninstitutional population of age 16 years and older	Macroeconomic	FR supervisory scenarios
Asset class	Indicator denoting asset class of the security	Security characteristic	FR Y-14Q
Coupon rate	Yield of security based on its face value	Security characteristic	Commercially available data
Effective rate/spread duration	The percentage change in price for a 100 basis point change in interest rate or option-adjusted spread	Security characteristic	Commercially available data
Market value	The price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date (FASB No. 157)	Security characteristic	FR Y-14Q
Maturity date	The date on which the security matures	Security characteristic	Commercially available data
Credit loss model			
Amortized cost (book value)	Purchase price of a debt security adjusted for the amortization of premium or accretion of discount if the debt security was purchased at other than par or face value	Security characteristic	FR Y-14Q
Asset class	Indicator denoting asset class of the security	Security characteristic	FR Y-14Q
Credit loss	Difference between the present value of cash flows and amortized cost	Security characteristic	FR Y-14Q
Market value	The price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date (FASB No. 157)	Security characteristic	FR Y-14Q, supervisory models

Note: Variables are listed alphabetically within variable type.

Trading and Private Equity

The trading and private equity model generates loss estimates related to trading and private equity positions held by firms that are subject to the global market shock. The trading model covers a wide range of firms' positions in asset classes such as public equity, foreign exchange, interest rates, commodities, securitized products, traded credit (e.g., municipals, auction rate securities, corporate credit, and sovereign credit), private equity, and other fair-value assets measured at mark-to-market. Trading P&L on firms' positions is determined as a function of a shock to one or more risk factors and firm-supplied information on initial positions and sensitivities to those risk-factor shocks.[70]

The model applies risk-factor shocks to firm-supplied exposures in one of two ways. For certain asset classes, including securitized products, private equity, other fair-value assets, and some traded credit items, loss projections are a function of direct haircuts to the market value of the asset. For these asset classes, the trading P&L for a firm is the product of the market value of the exposure and the relevant shock.[71]

For other assets in the trading book, such as foreign exchange, public equity, interest rate products, commodities, and most traded credit items, P&L is jointly determined by shocks to one or more risk factors. For these trading book assets, several risk factors may be needed to estimate P&L.[72] For cases in which the P&L is jointly determined, the model aggregates P&L over all applicable shocks.[73]

Total P&L projected for a firm is the sum of dollar changes associated with each shock that is relevant to the value of the position, aggregated for all trading and private equity portfolios.

Consistent with the Federal Reserve's modeling principles, losses from trading and private equity are recognized in the first quarter of the projection horizon.

Incremental Default Risk

The trading IDR model captures the risk of losses arising over the full nine-quarter projection horizon from a jump-to-default of issuers of debt securities in the trading book. The model estimates the potential for losses in a severe stress scenario that could arise from concentration risk in credit exposures held in the trading book.

The model measures jump-to-default losses in excess of mark-to-market losses calculated by the model used to project trading P&L. The exposure types captured in the IDR model include corporate, sovereign, agency, municipal, and securitization positions. These exposures span single-name products (e.g., corporate bonds and single-name credit default swaps (CDS)), index products, and index-tranche products. The IDR model projects quarterly losses on those exposures over the projection horizon of each stress test scenario.

Key variables that enter the model are

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70 The risk factors typically relevant for a large institution's trading portfolio include those relating to interest rates, option-adjusted spreads, energy and other commodity prices, equity prices, and credit spreads for the U.S. and other financially-developed countries.

71 An adjustment is made to the estimate of losses on private equity investments in affordable housing that qualify as Public Welfare Investments (PWI) under Regulation Y. See Appendix A for additional details.

72 For example, for foreign exchange positions, the relevant shocks would include shocks to the spot level of the exchange rate pair and to the volatility of the exchange rate.

73 The Federal Reserve collects aggregated data that capture changes in value of the positions with respect to many different values of each specified risk-factor shock. For example, firms may report sensitivities to a negative 30 percent, negative 25 percent, and 30 percent shock to a foreign exchange rate.

- through-the-cycle default probabilities for the debt issuers,
- long-run average LGD by asset class, and
- asset value correlation.

The model assumes that an obligor defaults when its asset value falls below a certain threshold that depends mainly on the initial rating of the obligor.[74] The model also assumes that changes in the value of an obligor's assets can be decomposed into an obligor-specific (idiosyncratic) component and a component common to all obligors. The common component enables the model to capture default correlation, as it implies that there is correlation in changes in obligor asset values and default probabilities.

The model simulates asset value paths for each obligor in a firm's portfolio. For a given simulated path, the model records a default if an obligor's stressed asset value falls below a specific model threshold. The model then calculates a loss by applying an asset-class LGD assumption to the exposure. The model repeats that process many times for each obligor, resulting in a distribution of losses.[75]

The model measures the projected loss as the loss associated with a percentile of the generated loss distribution. This percentile is related to the frequency of severe recessions.

IDR losses are calculated on net of mark-to-market trading losses under the global market shock for the portion of the relevant portfolio that is projected to default. The Federal Reserve applies the model at the level of each broad asset class.

Table 15. List of key variables in the trading incremental default risk model and sources of variables

Variable	Description	Variable type	Source
Asset correlation by asset classes	Asset value correlation used in Vasicek's model, which is a key determinant of the correlation of defaults among obligors	Asset class characteristic	Empirical and Basel capital standards
LGD by rating for asset classes	Long-run average loss given default, set by asset classes	Asset class characteristic	Commercially available data
PD by rating for asset classes	Empirical through-the-cycle default rates set by a rating agency for a given asset class	Asset class characteristic	Commercially available data
Obligor rating	Entity credit rating	Obligor characteristic	FR Y-14Q

Note: Variables are listed alphabetically within variable type.

Credit Valuation Adjustment

CVA is an adjustment to the mark-to-market valuation of a firm's exposures to its counterparties, taking into account PD and LGD for each counterparty. The CVA model captures the risk of credit losses arising from changes in exposures due to the effect of the global market shock on PD, LGD, and expected derivative exposures to counterparties.

[74] See Oldrich Alfons Vasicek, "The Distribution of Loan Portfolio Value," *Risk*, vol. 15 (December 2002): 160–62.

[75] In cases in which the firm's obligor data are collected in aggregate by rating for a given asset class, instead of granular obligor-level data on the FR Y-14Q schedule, the simulation uses obligor-size assumptions to proxy for obligor-level exposures.

The model is mainly based on firm-provided estimates of the components of stressed CVA. Those firm-provided components include

- discount factors,
- the expected exposure to counterparties,
- PD of counterparties, and
- LGD of counterparties.

The projected CVA loss in a supervisory scenario is the difference between the CVA projections in the supervisory stress scenario and those in the baseline (or unstressed) scenario. Consistent with the Federal Reserve's modeling principles, CVA losses are recognized in the first quarter of the projection horizon.

The model computes CVA by multiplying a positive expected exposure (EE) to a counterparty by its PD and LGD, and then discounts that expected valuation adjustment using a risk-free discount factor. EE is based on a 10-day margin period of risk assumption for all counterparties in cases in which margin is collected and excludes any additional margin collected due to the downgrade of a counterparty.[76] CVA is computed gross of any CVA hedges.

Specifically, in a supervisory stress scenario, the CVA model calculates a charge to a firm's derivative mark-to-market values over all the periods of contractual exposure using firm-provided inputs. These CVA charges are aggregated across all of the firm's counterparties using the following equation:

$$CVA(s) = \sum_k \sum_{t=1}^{T} DF(s,t,k) * EE(s,t,k) * PD(s,t,k) * LGD(s,k), \tag{24}$$

where s represents the supervisory scenario, t represents time, k represents a firm's counterparties, $CVA(s)$ represents the stressed CVA, $DF(s,t,k)$ represents the discount factor (DF), $EE(s,t,k)$ represents an expected exposure, $PD(s,t,k)$ represents the counterparty's probability of default, and $LGD(s,k)$ represents loss given default. In general, firm-provided PDs and LGDs are market-implied and consistent with pricing observed in the CDS market. The CVA charge only takes into consideration the default probability of the counterparty. There is no consideration of debt valuation adjustment when estimating CVA losses.

The model adjusts the CVA charge computed in equation (24) in order to account for data limitations and additional or offline reserves. The Federal Reserve collects CVA component data (i.e., EE, DF, PD, and LGD) for a subset of firms' counterparties that represent 95 percent or more of total unstressed CVA. The model adjusts the value in equation (24) to account for the risk associated with remaining counterparties, based on the ratio of the firm-provided aggregate CVA and the sum of CVA for the subset of counterparties.[77] Finally, the model adjusts the CVA projection for firm-reported additional or offline scenario-specific CVA reserves to arrive at a final projection of CVA under each scenario.[78]

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[76] The 10-day margin period of risk assumption implies that no margin payments are made for a 10-day period.

[77] This subset of counterparties reported at the counterparty level includes the firm's top counterparties, as ranked by unstressed CVA, and comprises at least 95 percent of total unstressed CVA.

[78] The model does not take the funding valuation adjustment into account in the CVA loss estimation process.

The Federal Reserve uses the trading and private equity model to calculate gains or losses on firms' CVA hedges.[79] The calculation of gains or losses on CVA hedges uses the same methodology as the calculation for trading book positions.

Table 16. List of key variables in the credit valuation adjustment model and sources of variables

Variable	Description	Variable type	Source
Counterparty-level EE profile (baseline and stressed)	Expected Exposure used to calculate CVA for each tenor bucket	Counterparty characteristic	FR Y-14Q
Counterparty-level LGD (baseline and stressed)	Market-implied LGD	Counterparty characteristic	FR Y-14Q
Counterparty-level PD (baseline and stressed)	Marginal PD between time t-1 and t	Counterparty characteristic	FR Y-14Q
Discount factor (baseline and stressed)	Firm-provided discount factor used to calculate CVA. The discount factor should be roughly equal to e^{-zt} or $(1+z)^{-t}$, where z is the value of the zero curve at time t for the risk-free rate	Counterparty characteristic	FR Y-14Q
Additional/offline CVA reserves (baseline and stressed)	Additional/offline CVA reserves, including risks not in CVA, wrong-way risk, offline reserves, or any other applicable, non-standard add-ons, that are not explicitly included in the EE profile on sub-schedule L.2	Firm characteristic	FR Y-14Q
Aggregate CVA data by ratings and collateralization (baseline and stressed)	Firm-provided and firm-wide total CVA excluding the additional/offline CVA reserves, consisting of CVA values by collateralized netting sets sorted by internal rating	Firm characteristic	FR Y-14Q

Note: Variables are listed alphabetically within variable type.

Largest Counterparty Default

The Federal Reserve applies the LCPD scenario to firms with substantial trading or custodial operations. The LCPD captures the risk of losses due to an unexpected default of the counterparty whose default would generate the largest stressed losses for a firm.

Firms subject to the LCPD scenario apply the global market shock to their counterparty exposures across derivatives positions as well as securities lending and borrowing positions and repurchase agreements (collectively known as SFTs), and the value of any associated collateral, as of the effective date of the market shock.

The notional amount of any single-name CDS hedges on the relevant counterparty is subtracted from stressed net current exposure, and the result is then multiplied by one minus the recovery rate, which is assumed to be 10 percent of the total stressed exposure.[80] Finally, the stressed CVA attributed to the counterparty is subtracted from the resulting loss. Formally, the net default loss can be expressed as

$$SN\ Loss(s,k) = \left(Total\ SN\ CE(s,k) - CDS\ Ntn(k)\right) * (1 - RR) - CVA(s,k), \quad (25)$$

where s represents the supervisory scenario, k represents the counterparty, $SN\ Loss(s,k)$ represents a firm's stressed net default loss to counterparty k in scenario s, $Total\ SN\ CE(s,k)$ represents stressed net current exposure to counterparty k in scenario s, $CDS\ Ntn(k)$ repre-

[79] The Federal Reserve collects information on these positions separately from and in the same format as information on other trading positions.

[80] The current assumption is an estimate of a potential stressed recovery rate for an undiversified credit exposure under severe market conditions.

sents the notional amount of CDS hedges on counterparty k, RR represents the assumed recovery rate, and $CVA(s,k)$ represents the stressed CVA associated with counterparty k in scenario s.

The model calculates equation (25) for all reported counterparties and ranks stressed net losses from largest to smallest. The loss attributable to the LCPD component in scenario s is set equal to the largest counterparty-level loss.[81]

Consistent with the Federal Reserve's modeling principles, LCPD losses are recognized in the first quarter of the projection horizon.

Table 17. List of key variables in the largest counterparty default model and sources of variables

Variable	Description	Variable type	Source
CDS hedge notional	The notional amount of single-name or index CDS hedges held by the firm that references the firm-reported counterparty	Counterparty characteristic	FR Y-14Q
Stressed CVA FR scenario	The CVA for the derivatives transactions held with a given counterparty as revalued under the global market shock	Counterparty characteristic	FR Y-14Q
Total stressed net CE FR scenario	Valuation of the counterparty portfolio across derivatives positions and SFTs after applying the global market shock. Firms are required to revalue both exposures and non-cash collaterals (posted and received) and to account for any close-out netting agreements in place. For a single netting agreement, this is calculated as the greater of zero and the difference between the aggregate stressed mark-to-market value of derivatives and securities or cash posted to the counterparty legal entity, and the aggregate stressed mark-to-market value of derivatives and securities or cash received from that counterparty legal entity. This amount captures all exposures (both SFTs and derivatives) to a consolidated/parent counterparty, and firms are required to report once at the legal entity level	Counterparty characteristic	FR Y-14Q

Note: Variables are listed alphabetically within variable type.

Calculation of Regulatory Capital Ratios

The models discussed previously generally project yields or loss rates, which the Federal Reserve scales by balances to arrive at levels of income and loss projections.[82]

The final modeling step incorporates these projections of revenues, expenses, losses, and provisions into calculations of regulatory capital for each firm under the supervisory scenarios. Regulatory capital is calculated using the definitions of capital in the Board's regulatory capital rule.[83] Regulatory capital is calculated consistent with the requirements that will be in

[81] Certain entities are excluded from the selection of a firm's largest counterparty, including Canada, France, Germany, Italy, Japan, the United Kingdom, the United States, and qualifying central counterparties (CCP) as defined in the regulatory capital rules (12 C.F.R. § 217.2 (2019)). For an intermediate holding company (IHC), affiliate counterparties, as they are defined in the U.S. final rule for Single Counterparty Credit Limits pursuant to the Dodd-Frank Act, are also excluded from the selection of its largest counterparty.

[82] The Federal Reserve generally projects that a firm takes actions to maintain its current level of assets, including its securities, trading assets, and loans, over the projection horizon. The Federal Reserve assumes that a firm's risk-weighted assets and leverage ratio denominators remain unchanged over the projection horizon, except for changes primarily related to items subject to deduction from regulatory capital or due to changes to the Board's regulations.

[83] See 12 C.F.R. pt. 217 (2019).

effect during the projected quarter of the projection horizon.[84] The definition of regulatory capital changes throughout the projection horizon in accordance with the transition arrangements in the revised regulatory capital framework, where applicable.[85]

Regulatory capital incorporates estimates of pre-tax net income from supervisory projections of revenues, expenses, losses, and provisions and is adjusted for tax expenses/benefits. To calculate current and deferred tax expenses/benefits, the Federal Reserve assumes all pre-tax net income to be taxable within the U.S. and subject to a consistent tax rate equal to the U.S. federal corporate tax rate of 21 percent.[86] In a specific quarter, the tax expense/benefit includes changes to the deferred tax asset (DTA) valuation allowance, which is comprised of a calculation that evaluates whether a firm will have sufficient taxable income to realize its DTAs. The model calculates tax expenses/benefits as

$$tax(t) = 21\% * PTNI(t) + \Delta VA(t), \tag{26}$$

where t represents time, $tax(t)$ represents the tax expense/benefit, $PTNI(t)$ represents pre-tax net income in projection quarter t, and $\Delta VA(t)$ represents the change in the valuation allowance, which evaluates whether a firm will have sufficient taxable income over the next year to realize its DTAs from temporary differences.[87] An increase in the valuation allowance indicates that more of the firm's DTAs will be unable to be used.

Two types of DTAs are projected: DTAs from net operating loss (NOL) carryforwards and DTAs from temporary differences. The Federal Reserve projects changes in net DTAs from NOLs when taxable income is negative.[88] Tax law imposes an 80 percent limit on the use of NOL carryforwards to offset current taxes, and the Federal Reserve imposes that limitation in the supervisory calculations. The Federal Reserve projects changes in net DTAs from temporary differences when there is a temporary difference between the GAAP and tax basis for income. In the supervisory calculation, the Federal Reserve projects net DTAs from temporary differences from OCI associated with AFS securities and the difference between the amount of loan losses booked for GAAP (i.e., loan-loss provisions) and the amount of loan losses recognized for tax purposes (i.e., net charge-offs).

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[84] See 12 C.F.R. § 225.8(e)(2)(i)(A) (2019) and 12 C.F.R. § 252.56(a)(2) (2019).

[85] See 12 C.F.R. pt. 217, subpt. G (2019).

[86] For a discussion of the effect of changing this tax rate assumption, see Board of Governors of the Federal Reserve System, *Dodd-Frank Act Stress Test 2013: Supervisory Stress Test Methodology and Results* (Washington: Board of Governors, March 2013), box 2, https://www.federalreserve.gov/newsevents/press/bcreg/dfast_2013_results_20130314.pdf. For an explanation of modifications to the calculation of projected capital to account for the passage of the Tax Cuts and Jobs Act in December 2017, see Board of Governors of the Federal Reserve System, *Dodd-Frank Act Stress Test 2018: Supervisory Stress Test Methodology and Results* (Washington: Board of Governors, June 2018), box 2, https://www.federalreserve.gov/publications/files/2018-dfast-methodology-results-20180621.pdf.

[87] This one-year look-ahead is equal to the look forward period for determining the appropriate level of allowance for expected credit losses on loans, as loan timing differences are the primary driver of projected temporary differences. DTAs from net operating losses (NOLs) are not evaluated for a potential valuation allowance because DTAs from NOLs are fully deducted from regulatory capital.

[88] The Federal Reserve calculates taxable income as PPNR plus realized gains and losses on HTM and AFS securities less net charge-offs and other losses, including trading and counterparty losses and losses on loans held under the fair-value option.

The quarterly change in CET1 capital before adjustments and deductions equals projected after-tax net income minus certain capital distributions (i.e., preferred dividends) plus other changes in equity capital, such as OCI and income attributable to minority interest.[89]

Projected regulatory capital levels are calculated under the applicable regulatory capital framework to incorporate, as appropriate, projected levels of non-common capital and certain items that are subject to adjustment or deduction in capital.[90] The Federal Reserve assumes most items that are subject to adjustment or deduction in capital and non–common capital remain constant at their starting value over the projection horizon. A similar approach is taken for income attributable to minority interest. The Federal Reserve projects other items subject to deduction, including DTAs, under each supervisory scenario. The Federal Reserve adjusts its projection of certain deduction items to reflect the impact of the global market shock.

The Federal Reserve combines projections of regulatory capital levels with projections of total assets for the leverage ratio, total assets and off-balance sheet exposures for the supplementary leverage ratio, and RWAs to calculate regulatory capital ratios. The risk-based regulatory capital ratios use RWAs calculated under the standardized approach.[91] The Federal Reserve assumes that a firm's RWAs and leverage ratio denominators remain unchanged over the projection horizon, except for changes primarily related to items subject to deductions from regulatory capital. The Federal Reserve adjusts the starting capital ratio denominators for items subject to adjustment or deduction from capital, consistent with the projection of each item in the numerator of the regulatory capital ratios and the regulatory capital requirements. Projected capital levels and ratios are not adjusted to account for any differences between projected and actual performance of firms observed at the time the supervisory stress test results are produced. The Federal Reserve assumes that a firm's RWAs and leverage

[89] The Federal Reserve uses the following capital action assumptions in projecting post-stress capital levels and ratios: (1) no dividends on any instruments that qualify as common equity tier 1 (CET1) capital; (2) all payments on instruments that qualify as additional tier 1 capital or tier 2 capital are equal to the stated dividend, interest, or principal due on such instruments; (3) no redemption or repurchase of any capital instrument that is eligible for inclusion in the numerator of a regulatory capital ratio; and (4) no issuances of common stock or preferred stock.

[90] The federal bank regulatory agencies issued a final rule on July 9, 2019, that reduces regulatory burden by simplifying several requirements in the agencies' regulatory capital rules; see Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, and Office of the Comptroller of the Currency, "Agencies Simplify Regulatory Capital Rules," joint press release, July 9, 2019, https://www.federalreserve.gov/newsevents/pressreleases/bcreg20190709a.htm.

The Federal Reserve Board issued a final rule on October 10, 2019, that tailors its regulations for domestic and foreign banks to more closely match their risk profiles; see Board of Governors of the Federal Reserve System, "Federal Reserve Board Finalizes Rules That Tailor Its Regulations for Domestic and Foreign Banks to More Closely Match Their Risk Profiles," press release, October 10, 2019, https://www.federalreserve.gov/newsevents/pressreleases/bcreg20191010a.htm.

Additionally, the Federal Reserve Board issued a final rule on March 4, 2020, that simplified the capital rules for large banks, see 12 C.F.R. pts. 217, 225, and 252 (2020); the Federal Register notice is available on the Board's website at https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20200304a2.pdf.

For additional information, see also Board of Governors of the Federal Reserve System, "Federal Reserve Board Approves Rule to Simplify Its Capital Rules for Large Banks, Preserving the Strong Capital Requirements Already in Place," press release, March 4, 2020, https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200304a.htm. As firms subject to Category III standards will only be subject to the transitions freeze capital rule for only one quarter, Q1 2020, the supervisory projection of regulatory capital does not include the transitions freeze calculation for firms subject to Category III standards.

[91] See 12 C.F.R. pt. 217 (2019).

ratio denominators remain unchanged over the projection horizon except for changes primarily related to items subject to deductions from regulatory capital. The Federal Reserve adjusts starting standardized RWAs and leverage ratio denominators for items subject to adjustment or deduction from capital, consistent with the projection of each item in the numerator of the regulatory capital ratios and the regulatory capital requirements. Projected capital levels and ratios are not adjusted to account for any differences between projected and actual performance of firms observed at the time the supervisory stress test results are produced.

Table 18. Treatment of key regulatory capital deductions and adjustments

Item/Description	Treatment	Source
Additional tier 1 capital deductions	Held constant	FR Y-14A; FR Y-9C
All other deductions from (additions to) CET1 capital before threshold-based deductions	Held constant[1]	FR Y-14A; FR Y-9C
AOCI-related adjustments	Held constant	FR Y-9C
Deductions applied to CET1 capital due to insufficient amounts of additional tier 1 capital and tier 2 capital to cover deductions	Held constant	FR Y-14A; FR Y-9C
DTAs arising from temporary differences that could not be realized through NOL carrybacks, net of related valuation allowance and net of DTLs	Supervisory projections	FR Y-14A and FR Y-14Q starting value
DTAs from NOLs and tax credit carryforwards, net of any related valuation allowances and net of DTLs	Supervisory projections	FR Y-14A and FR Y-14Q starting value
Goodwill, net of associated DTLs	Held constant[1]	FR Y-9C
Intangible assets (other than goodwill and mortgage servicing assets), net of associated DTLs	Held constant	FR Y-9C
Mortgage servicing assets, net of associated DTLs	Held constant	FR Y-14A and FR Y-14Q starting value
Non-significant investments in the capital of unconsolidated financial institutions in the form of common stock	Held constant[1]	FR Y-14A; Special data collection for starting value
Significant investments in the capital of unconsolidated financial institutions in the form of common stock	Held constant[1]	FR Y-14A and FR Y-14Q starting value
Tier 2 capital deductions	Held constant	FR Y-14A; FR Y-9C
Unrealized net gain (loss) related to changes in the fair value of liabilities that are due to changes in credit risk	Held constant	FR Y-9C
Income attributable to minority interest	Supervisory projections	FR Y-9C

[1] Certain items are adjusted to reflect the impact of the global market shock.

Modeled Loss Rates

Corporate Loan Model

Modeled Loss Rates on Pools of Corporate Loans

The output of the corporate loan model is the expected loss on each loan. As described above, estimated corporate loan loss rates depend on a number of variables. This section groups loans according to three of the most important variables in the model: sector (financial and nonfinancial), security status (secured and unsecured), and rating class (investment grade and non-investment grade).[92] Categorizing corporate loans reported on schedule H.1 of the FR Y-14Q as of the fourth quarter of 2018 by sector, security status, and rating class results in eight groups of loans:[93]

1. Financial, secured, investment grade
2. Financial, secured, non-investment grade
3. Financial, unsecured, investment grade
4. Financial, unsecured, non-investment grade
5. Nonfinancial, secured, investment grade
6. Nonfinancial, secured, non-investment grade
7. Nonfinancial, unsecured, investment grade
8. Nonfinancial, unsecured, non-investment grade

The remainder of this section reports summary statistics and modeled loss rates for these eight groups of corporate loans.

Table 19 reports summary statistics for the eight groups of loans. The summary statistics cover a wide set of variables that capture important characteristics of the loans and borrowers in the loan groups.

Table 20 shows the modeled loss rates for the eight groups of loans for the DFAST 2019 supervisory severely adverse scenario. Each entry in the table shows the portfolio-level (average) estimated loss rate for the loans in one of the eight groups, as well as the median and 25th and 75th percentiles of the estimated loan-level loss rates.

[92] Financial loans have a NAICS category ("naics_two_digit_cat") of 52; all other loans are marked nonfinancial. Secured loans are defined as loans with lien positions ("lien_position_cat") marked as "first-lien senior"; all other loans are marked as unsecured. Investment grade loans are defined as loans with a credit rating ("rating") higher than and including BBB; all other loans are marked as non-investment grade.

[93] The set of loans on which loss rates are calculated excludes loans held for sale or accounted for under the fair-value option, loan observations missing data fields used in the model, lines of credit that were undrawn as of 2018:Q4, and other types of loans that are not modeled using the corporate loan model. A notable change in the loan sample from last year is the inclusion of loans to financial depositories. These loans were not previously modeled using the corporate loan model.

Table 19. Summary statistics of selected variables in the corporate loan data grouped by loan and borrower characteristics

Percent as a share of utilized balance, except as noted

Variables	Non-investment grade				Investment grade			
	Nonfinancial sector		Financial sector		Nonfinancial sector		Financial sector	
	Unsecured	Secured	Unsecured	Secured	Unsecured	Secured	Unsecured	Secured
Number of loans (thousands)	14.20	105.44	2.35	9.46	21.30	46.26	3.40	6.38
Facility type								
Revolving	33.51	47.83	20.31	48.10	33.13	39.35	34.20	71.49
Term loan	46.93	36.79	27.93	20.58	44.25	40.00	32.49	15.26
Other	19.56	15.37	51.76	31.32	22.61	20.65	33.31	13.24
Credit rating[1]								
AAA	0.00	0.00	0.00	0.00	1.46	1.11	9.74	5.35
AA	0.00	0.00	0.00	0.00	7.47	8.01	5.49	10.08
A	0.00	0.00	0.00	0.00	22.37	21.74	23.60	38.74
BBB	0.00	0.00	0.00	0.00	68.71	69.15	61.18	45.83
BB	81.70	72.18	81.90	82.60	0.00	0.00	0.00	0.00
B	15.12	22.64	12.23	15.79	0.00	0.00	0.00	0.00
CCC or below	3.18	5.18	5.87	1.61	0.00	0.00	0.00	0.00
Lien position								
First-lien senior	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00
Senior unsecured	95.61	0.00	98.82	0.00	98.46	0.00	98.96	0.00
Other	4.39	0.00	1.18	0.00	1.54	0.00	1.04	0.00
Interest rate variability								
Fixed	22.61	14.72	25.61	5.86	24.68	27.98	19.30	6.95
Floating	75.68	80.11	59.97	92.35	72.64	68.39	74.14	89.53
Mixed	1.71	5.17	14.42	1.80	2.68	3.63	6.55	3.52
Industry[2]								
Agriculture, fishing, and hunting	0.59	1.31	0.00	0.00	0.30	0.62	0.00	0.00
Natural resources, utilities, and construction	11.74	8.78	0.00	0.00	9.47	5.60	0.00	0.00
Manufacturing	26.00	18.07	0.00	0.00	29.49	13.32	0.00	0.00
Trade and transportation	22.47	34.19	0.00	0.00	16.71	25.58	0.00	0.00
Technological and business services	29.04	22.15	0.00	0.00	27.19	20.67	0.00	0.00
Finance and insurance	0.00	0.00	100.00	100.00	0.00	0.00	100.00	100.00
Education, health care, and social assistance	3.79	5.34	0.00	0.00	7.27	13.37	0.00	0.00
Entertainment and lodging	2.62	5.96	0.00	0.00	1.73	4.26	0.00	0.00
Other services	3.73	4.20	0.00	0.00	7.84	16.59	0.00	0.00
Guarantor flag								
Full guarantee	42.50	47.64	16.79	33.65	32.95	32.62	25.39	13.01
U.S. government guarantee	5.51	0.36	2.02	0.14	0.37	0.76	0.56	0.03
Partial guarantee	2.14	2.58	1.49	3.61	1.32	1.74	2.57	3.42
No guarantee	49.85	49.42	79.70	62.60	65.36	64.88	71.48	83.54
Other loan characteristics								
Domestic obligor, share of utilized balance	55.79	91.87	26.61	76.02	69.71	90.68	39.60	79.18
Remaining maturity, average in months[3, 4]	39.48	48.44	16.41	26.98	35.09	55.48	32.73	28.18
Interest rate, average in percent[4]	4.12	4.59	3.82	4.06	3.54	3.68	3.94	3.78
Committed exposure, average in millions of dollars	15.31	9.32	22.90	21.20	29.47	13.11	46.52	66.93
Utilized exposure, average in millions of dollars	11.01	6.76	19.68	16.87	19.68	9.91	34.05	46.81

Note: The set of loans presented in this table excludes loans held for sale or accounted for under the fair-value option, loan observations missing data fields used in the model, lines of credit that were undrawn as of 2018:Q4, and other types of loans that are not modeled using the corporate loan model. A notable change in the loan sample from last year is the inclusion of loans to financial depositories. These loans were not previously modeled using the corporate loan model.

1 Credit ratings are derived from firm-reported internal credit ratings for borrowers and a firm-reported table that maps internal ratings to a standardized rating scale. The internal credit ratings of a small percentage of loans map to multiple standardized ratings. In such cases, exposures are divided proportionally and reported in this table as multiple loans.

2 Industries are collapsed using the first digit of the NAICS 2007 code, except for finance and insurance, which is broken out separately, and public administration, which is collapsed under other services.

3 Maturity excludes demand loans.

4 Averages for remaining maturity and interest rate are weighted by utilized exposure.

Table 20. Projected corporate loan portfolio loss rates and 25th and 75th percentile ranges by loan and borrower characteristics, 2019:Q1–2021:Q1, DFAST 2019 severely adverse scenario

Sector	Security status	Rating class	Loan-level loss rates (percent)			Portfolio-level loss rates (percent)
			25th	Median	75th	Average
Financial	Secured	Investment grade	1.3	3.6	4.9	3.1
Financial	Secured	Non-investment grade	4.6	5.8	7.2	6.9
Financial	Unsecured	Investment grade	0.7	1.8	5.8	2.7
Financial	Unsecured	Non-investment grade	1.1	3.4	7.8	4.4
Nonfinancial	Secured	Investment grade	0.4	0.6	1.4	1.0
Nonfinancial	Secured	Non-investment grade	3.7	4.5	12.0	6.7
Nonfinancial	Unsecured	Investment grade	0.6	1.0	2.1	1.1
Nonfinancial	Unsecured	Non-investment grade	2.8	5.1	12.6	5.7

Note: Loan-level loss rates are calculated as cumulative nine-quarter losses on a given loan divided by initial utilized balance on that loan. Portfolio-level loss rates are calculated as the sum of the cumulative nine-quarter losses divided by the sum of initial utilized balances. The set of loans on which loss rates are calculated excludes loans held for sale or accounted for under the fair-value option, loan observations missing data fields used in the model, lines of credit that were undrawn as of 2018:Q4, and other types of loans that are not modeled using the corporate loan model. A notable change in the loan sample from last year is the inclusion of loans to financial depositories. These loans were not previously modeled using the corporate loan model. The corporate loan model was modified to separately calibrate financial and non-financial obligors. See Appendix A for additional details.

Certain groups of loans generally have wider ranges of losses than other groups. Although the loans are grouped according to the most important characteristics in the model, other loan characteristics in the model also affect loss rates, albeit in a more limited manner. Differences in these other characteristics within each loan group are responsible for the range of loss rates shown in the tables. Greater variation in these other characteristics within a group will generally lead to larger ranges of loss rates. For example, among secured, non-investment grade loans, the range of loan-level loss rates is 4.6 to 7.2 for financial firms, compared to 3.7 to 12.0 for nonfinancial firms, which include a wider variety of industries (table 20). Secured, non-investment grade loans to nonfinancial firms are predominantly loans to firms in the manufacturing, transportation, and technology sectors but also include loans to firms in other sectors like education and utilities (table 19). The corporate loan model change described in Appendix A contributed to a decline in loss rates to financial sector loans.

Portfolios of Hypothetical Corporate Loans and Associated Loss Rates

The effect of loan and borrower characteristics on the losses estimated by the corporate loan model can also be illustrated by the differences in the estimated loss rates on specific sets of hypothetical loans. This section contains descriptive statistics from three portfolios of hypothetical corporate loans (table 22) and the modeled loss rates for the three portfolios under the DFAST 2019 supervisory severely adverse scenario (table 23).

The Federal Reserve has designed the portfolios of hypothetical loans to have characteristics similar to the actual loans reported in schedule H.1 of the FR Y-14Q. The Federal Reserve provides three portfolios containing 200 loans each, designed to capture characteristics associated with

1. typical set of loans reported in the FR Y-14Q,
2. higher-than-average-risk loans (in this case, non-investment grade loans), and
3. lower-than-average-risk loans (in this case, investment grade loans).

The portfolios of hypothetical loans include 12 variables that describe characteristics of corporate loans that are generally used to estimate corporate loan losses (table 21).[94]

Table 21. List of variables included in portfolios of hypothetical corporate loans

Variable	Mnemonic	Description
Facility type	facility_type_cat	The type of credit facility: 1 is revolving 7 is term loan 0 is other
Credit rating	rating	Credit rating of obligor. Categories include AAA, AA, A, BBB, BB, B, CCC, CC, C, and D
Lien position	lien_position_cat	The type of lien: 1 is first-lien senior 2 is second-lien 3 is senior unsecured 4 is contractually subordinated
Interest rate variability	interest_rate_variability	Interest rate type: 0 is fully undrawn (interest rate not provided) 1 is fixed 2 is floating 3 is mixed
Industry	naics_two_digit_cat	Two-digit industry code based on 2007 NAICS definitions
Guarantor flag	guarantor_flag	Indicates the type of guarantee of the guarantor: 1 is full guarantee 2 is partial guarantee 3 is U.S. government agency guarantee 4 is no guarantee
Domestic obligor	domestic_flag	Equal to 1 if obligor is domiciled in the U.S.
Remaining maturity	term	Remaining term of the loan in months
Interest rate	interest_rate	Interest rate on credit facility
Committed exposure	committed_exposure_amt	Committed exposure in dollars
Utilized exposure	utilized_exposure_amt	Utilized exposure in dollars
Origination year	orig_year	Year loan was originated

Note: Some of the variables included in the portfolios of hypothetical loans are presented in a more aggregated form than they are reported in the FR Y-14.

Table 22 contains summary statistics for the portfolios of hypothetical corporate loans in the same format as table 19. The portfolios of hypothetical loans are constructed to capture characteristics of certain sets of loans but are not fully representative of the population of loans reported in table 19. Table 23 contains the loss rates for the portfolios of hypothetical corporate loans calculated under the DFAST 2019 supervisory severely adverse scenario. The portfolio of higher-risk loans has higher loss rates under the severely adverse scenario (loss rate of 7.3 percent) than the portfolio of typical loans (loss rate of 5.0 percent) and the portfolio of lower-risk loans (loss rate of 1.9 percent).

[94] The sets of accounts are available for download on the Federal Reserve's website: higher-than-average-risk accounts, https://www.federalreserve.gov/supervisionreg/files/corporate-high-risk-2020.csv; typical-risk accounts, https://www.federalreserve.gov/supervisionreg/files/corporate-typical-2020.csv; lower-than-average-risk accounts, https://www.federalreserve.gov/supervisionreg/files/corporate-low-risk-2020.csv.

Table 22. Summary statistics of selected variables in the portfolios of hypothetical corporate loans
Percent as a share of utilized balance, except as noted

Variables	Lower-risk	Typical	Higher-risk
Facility type			
Revolving	55.56	45.19	30.80
Term loan	25.72	41.52	57.53
Other	18.71	13.29	11.67
Credit rating			
AAA	0.00	0.01	0.00
AA	1.47	1.87	0.00
A	32.97	2.65	0.00
BBB	65.56	28.22	0.00
BB	0.00	58.86	84.04
B	0.00	7.28	15.69
CCC or below	0.00	1.10	0.27
Lien position			
First-lien senior	59.35	70.19	90.05
Senior unsecured	40.65	29.81	9.63
Other	0.00	0.00	0.32
Interest rate variability			
Fixed	17.49	9.07	15.41
Floating	82.51	90.93	84.59
Mixed	0.00	0.00	0.00
Industry[1]			
Agriculture, fishing, and hunting	0.00	0.47	0.63
Natural resources, utilities, and construction	4.26	12.57	1.84
Manufacturing	9.98	18.56	21.48
Trade and transportation	27.68	11.97	22.30
Technological and business services	5.11	24.28	14.54
Finance and insurance	21.32	20.41	23.01
Education, health care, and social assistance	14.55	5.93	4.93
Entertainment and lodging	6.00	3.01	8.52
Other services	11.09	2.80	2.75
Guarantor flag			
Full guarantee	31.36	43.91	52.85
U.S. government guarantee	0.00	0.15	0.31
Partial guarantee	0.00	0.56	0.40
No guarantee	68.64	55.38	46.44
Other loan characteristics			
Domestic obligor, share of utilized balance	91.18	79.95	75.42
Remaining maturity, average in months[2,3]	36.83	28.40	45.14
Interest rate, average in percent[3]	2.92	3.28	4.30
Committed exposure, average in millions of dollars	23.36	14.71	12.98
Utilized exposure, average in millions of dollars	10.39	8.43	6.66

1 Industries are collapsed using the first digit of the NAICS 2007 code, except for finance and insurance, which is broken out separately, and public administration, which is collapsed under other services.

2 Maturity excludes demand loans.

3 Averages for remaining maturity and interest rate are weighted by utilized exposure.

Table 23. Projected corporate loan portfolio loss rates, 2019:Q1–2021:Q1, DFAST 2019 severely adverse scenario
Percent

Hypothetical portfolio	Loss rate
Lower-risk	1.9
Typical	5.0
Higher-risk	7.3

Note: Portfolio-level loss rates are calculated as the sum of the cumulative nine-quarter losses divided by the sum of initial utilized balances.

Commercial Real Estate Loan Model

Modeled Loss Rates on Pools of CRE Loans

The output of the CRE loan model is the expected loss on each loan. As described above, estimated CRE loan loss rates depend on a number of variables. This section groups loans according to four of the most important variables in the model: the broad loan category (construction and income-producing loans), time to maturity, property type, and LTV ratio at origination. CRE loans reported on schedule H.2 of the FR Y-14Q as of the fourth quarter of 2018 are segmented by broad loan category, time to maturity, property type, and LTV ratio at origination into nine groups of CRE loans:[95]

1. Construction loans
2. Time to maturity of three years or less; income-producing loans backed by hotel, retail, or office properties; LTV ratio at origination of 70 percent or below
3. Time to maturity of three years or less; income-producing loans backed by hotel, retail, or office properties; LTV ratio at origination of more than 70 percent
4. Time to maturity of three years or less; income-producing loans backed by other property types; LTV ratio at origination of 70 percent or below
5. Time to maturity of three years or less; income-producing loans backed by other property types; LTV ratio at origination of more than 70 percent
6. Time to maturity of more than three years; income-producing loans backed by hotel, retail, or office properties; LTV ratio at origination of 70 percent or below
7. Time to maturity of more than three years; income-producing loans backed by hotel, retail, or office properties; LTV ratio at origination of more than 70 percent
8. Time to maturity of more than three years; income-producing loans backed by other property types; LTV ratio at origination of 70 percent or below
9. Time to maturity of more than three years; income-producing loans backed by other property types; LTV ratio at origination of more than 70 percent

[95] The set of loans presented in this table excludes loans held for sale or accounted for under the fair-value option, loan observations lacking enough reported information to be assigned a modeled loss rate, loans that were in default or had no outstanding or committed balance remaining as of 2018:Q4, and other types of loans that are not modeled using the CRE loan model.

The remainder of this section reports summary statistics and modeled loss rates for these nine groups of CRE loans.

Table 24 reports summary statistics for the nine groups of loans. The summary statistics cover a wide set of variables that capture important characteristics of the loans and borrowers in the loan groups.

Table 24. Summary statistics of selected variables in the CRE loan data grouped by loan and borrower characteristics

Percent as a share of utilized balance, except as noted

Variables	Construction	Time to maturity of 3 years or less				Time to maturity of greater than 3 years			
		Hotel, retail, and office		Other property types		Hotel, retail, and office		Other property types	
		Loan-to-value at origination		Loan-to-value at origination		Loan-to-value at origination		Loan-to-value at origination	
		70% or less	Above 70%	70% or less	Above 70%	70% or less	Above 70%	70% or less	Above 70%
Number of loans (thousands)	11.50	5.19	1.37	4.17	1.17	10.91	2.27	27.46	4.05
Origination balance									
Less than $2 million	2.96	2.48	2.58	3.88	3.36	4.83	4.56	13.33	8.92
$2 million–$4.999 million	5.30	6.32	7.80	9.24	8.57	11.38	11.87	24.37	17.41
$5 million–$9.999 million	7.76	6.94	10.06	11.55	10.44	10.93	11.44	17.30	16.40
$10 million or greater	83.98	84.26	79.56	75.32	77.63	72.86	72.13	45.00	57.27
Current collateral value									
Less than $4 million	3.96	2.30	6.35	2.78	6.33	4.37	8.55	12.11	15.16
$4 million–$9.999 million	4.97	5.58	11.02	8.23	10.92	10.94	13.53	23.74	19.70
$10 million–$19.999 million	8.19	7.10	10.89	11.47	15.71	11.39	13.89	18.07	17.63
$20 million or greater	82.88	85.02	71.74	77.53	67.04	73.30	64.04	46.08	47.50
Property type									
Hotel	6.81	19.53	10.54	0.00	0.00	15.16	11.98	0.00	0.00
Office	11.08	50.72	56.86	0.00	0.00	52.08	60.23	0.00	0.00
Retail	6.43	29.76	32.60	0.00	0.00	32.75	27.79	0.00	0.00
Industrial	5.11	0.00	0.00	15.43	12.24	0.00	0.00	11.00	17.07
Multi-family	44.22	0.00	0.00	57.69	57.70	0.00	0.00	76.33	67.45
Other	26.34	0.00	0.00	26.87	30.06	0.00	0.00	12.67	15.48
Census region									
Midwest	7.81	9.43	18.76	8.73	21.41	7.53	14.15	8.22	15.85
Northeast	23.42	25.28	18.19	29.13	29.77	23.99	24.72	25.11	25.69
South	37.76	32.84	34.89	34.88	27.16	31.48	33.02	14.57	24.34
West	31.00	32.45	28.16	27.26	21.65	37.00	28.10	52.10	34.13
Origination year									
2015 and prior	21.39	47.96	50.40	46.52	46.36	27.54	25.27	33.73	41.39
2016	29.73	23.92	21.07	19.96	21.61	17.37	15.58	20.65	18.74
2017	28.30	14.35	14.12	13.74	14.92	23.24	23.81	20.01	15.76
2018	20.58	13.77	14.40	19.78	17.11	31.85	35.35	25.61	24.12

Note: The set of loans presented in this table excludes loans held for sale or accounted for under the fair-value option, loan observations missing data fields used in the model, and loans that were in default or had no outstanding or committed balance remaining as of 2018:Q4, and other types of loans that are not modeled using the CRE loan model.

Table 25 shows the modeled loss rates for the nine groups of CRE loans for the DFAST 2019 supervisory severely adverse scenario. Each entry in the table shows the portfolio-level (average) estimated loss rate for the loans in one of the nine groups, as well as the median and 25th and 75th percentiles of the estimated loan-level loss rates.

Table 25. Projected CRE portfolio loss rates and 25th and 75th percentile ranges by loan and borrower characteristics, 2019:Q1–2021:Q1, DFAST 2019 severely adverse scenario

Time to maturity	Property type	Loan-to-value at origination	Loan-level loss rates (percent)			Portfolio-level loss rates (percent)
			25th	Median	75th	Average
Three years or less	Hotel, retail, and office	70% or below	1.1	2.4	8.0	9.7
Three years or less	Hotel, retail, and office	Above 70%	1.7	3.9	12.8	16.1
Three years or less	Other property types	70% or below	0.6	1.2	3.5	5.1
Three years or less	Other property types	Above 70%	1.0	2.0	6.8	9.9
Greater than three years	Hotel, retail, and office	70% or below	0.3	0.5	1.5	2.6
Greater than three years	Hotel, retail, and office	Above 70%	0.4	0.9	2.6	5.3
Greater than three years	Other property types	70% or below	0.1	0.2	0.3	0.8
Greater than three years	Other property types	Above 70%	0.2	0.3	0.8	2.0
Construction loans			0.6	2.2	8.3	9.9

Note: Loan-level loss rates are calculated as cumulative nine-quarter losses on a given loan divided by initial utilized balance on that loan.

Portfolio-level loss rates are calculated as the sum of the cumulative nine-quarter losses divided by the sum of initial utilized balances. The set of loans presented in this table excludes loans held for sale or accounted for under the fair-value option, loan observations missing data fields used in the model, and loans that were in default or had no outstanding or committed balance remaining as of 2018:Q4, and other types of loans that are not modeled using the CRE loan model.

The loans are grouped according to the most important characteristics in the model, but combinations of other loan characteristics in the model can also affect loss rates given the idiosyncratic nature of CRE lending risk. For example, loans collateralized by highly priced properties in markets with relatively high vacancy rates would experience outsized losses under stress as that collateral would be relatively illiquid during a downturn. Those idiosyncratic risks can result in outsized projected stress losses on a given loan, relative to other more typical loans in a segment. This feature of the market results in average loan loss rates that can be higher than the 75th percentile loan loss rates.

Portfolios of Hypothetical CRE Loans and Associated Loss Rates

The effect of loan and borrower characteristics on the losses estimated by the CRE model can also be illustrated by the differences in the estimated loss rates on specific sets of hypothetical loans. This section contains descriptive statistics from three portfolios of hypothetical CRE loans (table 27) and the modeled loss rates for the three portfolios under the DFAST 2019 supervisory severely adverse scenario (table 28).

The Federal Reserve has designed the portfolios of hypothetical loans to have characteristics similar to the actual loans reported in schedule H.2 of the FR Y-14Q. The Federal Reserve provides three portfolios containing 200 loans each, designed to capture characteristics associated with

1. typical set of loans reported in the FR Y-14Q,
2. higher-than-average-risk loans (in this case, loans with time to maturity of three years or less), and
3. lower-than-average-risk loans (in this case, loans with time to maturity of more than three years).

The portfolios of hypothetical loans include 10 variables that describe characteristics of CRE loans that are generally used to estimate CRE losses (table 26).[96]

Table 27 contains summary statistics for the portfolios of hypothetical CRE loans in the same format as table 24. The portfolios of hypothetical loans are constructed to capture characteristics of certain sets of loans but are not fully representative of the population of loans reported in table 24. Table 28 contains the loss rates for the portfolios of hypothetical CRE loans calculated under the DFAST 2019 supervisory severely adverse scenario. The portfolio of higher-risk loans has higher loss rates under the severely adverse scenario (loss rate of 13.0 percent) than the portfolio of typical loans (loss rate of 4.8 percent) and the portfolio of lower-risk loans (loss rate of 2.4 percent).

Table 26. List of variables included in portfolios of hypothetical CRE loans

Variable	Mnemonic	Description
Current committed balance	committed_balance_amt	Current committed balance in dollars
Current outstanding balance	outstanding_balance_amt	Current outstanding balance in dollars
Origination balance	model_origination_balance_amt	Origination balance in dollars
Current collateral value	value_current_amt	Collateral value as of 2018:Q4 in dollars
LTV at origination	ltv_at_origination	Loan-to-value ratio at the origination of loan
Broad loan-type category	broad_loan_type_cat	Loan type categorization: categories are "construction" and "income-producing"
Property type	prop_type	Property types:
		1 is retail
		2 is industrial
		3 is hotel
		4 is multi-family
		5 is office
		6 is other
State code	state_cd	Two digit integer code for state that the property is located in
Year of origination	orig_year	Year that the loan was originated
Maturity date	dt_maturity	Maturity date of loan

Note: Some of the variables included in the portfolios of hypothetical loans are presented in a more aggregated form than they are reported in the FR Y-14.

[96] The sets of accounts are available for download on the Federal Reserve's website: higher-than-average-risk accounts, https://www.federalreserve.gov/supervisionreg/files/cre-high-risk-2020.csv; typical-risk accounts, https://www.federalreserve.gov/supervisionreg/files/cre-typical-2020.csv; lower-than-average-risk accounts, https://www.federalreserve.gov/supervisionreg/files/cre-low-risk-2020.csv.

Table 27. Summary statistics of selected variables in the portfolios of hypothetical CRE loans
Percent as a share of utilized balance, except as noted

Variables	Lower-risk	Typical	Higher-risk
Origination balance			
Less than $2 million	9.89	6.07	1.96
$2 million–$4.999 million	17.78	15.63	4.75
$5 million–$9.999 million	15.03	16.13	8.54
$10 million or greater	57.30	62.16	84.75
Current collateral value			
Less than $4 million	8.05	6.09	1.63
$4 million–$9.999 million	18.92	20.40	5.19
$10 million–$19.999 million	19.03	15.39	11.59
$20 million or greater	54.00	58.12	81.60
Property type			
Hotel	8.02	7.29	18.00
Office	29.01	13.75	23.43
Retail	11.41	8.83	12.20
Industrial	7.32	2.78	2.28
Multi-family	37.46	47.81	36.30
Other	6.79	19.55	7.80
Census region			
Midwest	11.83	5.58	10.20
Northeast	32.02	20.20	24.05
South	20.03	38.38	31.75
West	36.12	35.84	34.01
Origination year			
2015 and prior	36.18	28.68	36.72
2016	23.29	18.35	29.09
2017	20.31	20.87	9.18
2018	20.23	32.11	25.01

Table 28. Projected CRE portfolio loss rates, 2019:Q1–2021:Q1, DFAST 2019 severely adverse scenario
Percent

Hypothetical portfolio	Loss rate
Lower-risk	2.4
Typical	4.8
Higher-risk	13.0

Note: Portfolio-level loss rates are calculated as the sum of the cumulative nine-quarter losses divided by the sum of initial utilized balances.

Domestic First-Lien Residential Mortgage Model

Modeled Loss Rates on Pools of First-Lien Mortgages

The output of the first-lien mortgage model is the expected loss on each loan. As described above, estimated first-lien mortgage loss rates depend on a number of variables. In this section, loans are segmented according to two of the most important variables in the model: the LTV ratio at origination and the borrower's commercially available credit score. FICO®

Scores are the most widely used commercially available credit scores in the historical data used to estimate the model.[97] First-lien mortgages reported on schedule A.1 of the FR Y-14M as of the fourth quarter of 2018 are segmented by LTV ratio and FICO® Score into six groups of loans:[98]

1. Loans with LTV ratio of 80 percent or less and borrower FICO® Score under 680
2. Loans with LTV ratio of 80 percent or less and borrower FICO® Score between 680 and 739
3. Loans with LTV ratio of 80 percent or less and borrower FICO® Score of 740 or greater
4. Loans with LTV ratio of more than 80 percent and borrower FICO® Score under 680
5. Loans with LTV ratio of more than 80 percent and borrower FICO® Score between 680 and 739
6. Loans with LTV ratio of more than 80 percent and borrower FICO® Score of 740 or greater

The remainder of this section reports summary statistics and modeled loss rates for these six groups of first-lien mortgages.

Table 29 reports summary statistics for the six groups of loans. The summary statistics cover a wide set of variables that capture important characteristics of the loans and borrowers in the loan groups.

Table 29. Summary statistics of selected variables in the first-lien mortgage data grouped by loan and borrower characteristics

Percent as a share of unpaid principal balance, except as noted

Variables	Loan-to-value at origination					
	80% or less			Greater than 80%		
	Credit score (FICO® Score)[1]			Credit score (FICO® Score)[1]		
	Under 680	680 to 739	740 and over	Under 680	680 to 739	740 and over
Number of loans (thousands)	290.26	551.52	1702.36	182.96	144.37	212.73
Current unpaid balance						
$200,000 and Less	23.74	10.89	7.20	61.89	31.89	12.88
$200,001–$400,000	16.18	12.50	9.80	21.58	21.36	14.96
Over $400,000	60.08	76.61	83.00	16.53	46.75	72.16
Payment status						
Current (0–89 days past due)	98.70	99.66	99.94	97.11	99.33	99.89
Late (90–180 days past due)	1.30	0.34	0.06	2.89	0.67	0.11

(continued)

[97] FR Y-14 reporters are not required to report a particular credit score. For the purposes of making projections using a model estimated with FICO® Scores, the Federal Reserve maps scores reported on the FR Y-14 to FICO® Scores.

[98] The set of loans presented in this table excludes loans held for sale or accounted for under the fair-value option, loan observations missing data fields used in the model, loans that were in default or had no unpaid balance remaining as of 2018:Q4, loans that were purchased credit-impaired, and other types of loans that are not modeled using the domestic first-lien mortgage model (e.g., commercial loans).

Table 29.—*continued*

Variables	Loan-to-value at origination					
	80% or less			Greater than 80%		
	Credit score (FICO® Score)[1]			Credit score (FICO® Score)[1]		
	Under 680	680 to 739	740 and over	Under 680	680 to 739	740 and over
Occupancy type						
Primary	72.66	86.87	86.88	94.48	94.81	94.45
Second home	22.04	9.80	10.05	3.44	4.01	4.71
Investment	4.98	3.25	3.03	1.38	1.03	0.79
Unknown	0.32	0.07	0.04	0.70	0.15	0.06
Product						
Fixed rate mortgage	42.80	56.54	62.69	71.11	72.38	73.52
Adjustable-rate mortgage	57.20	43.46	37.31	28.89	27.62	26.48
Property type						
Single	79.23	85.66	84.56	87.84	87.75	88.86
Condo/Co-op	16.69	11.86	13.37	6.55	8.37	9.36
2–4 units	2.70	2.01	1.78	3.18	2.25	0.94
Other	1.39	0.47	0.30	2.43	1.63	0.84
Loan purpose						
Purchase	36.02	40.40	49.23	53.39	66.12	75.87
Refinance	27.96	34.03	32.50	17.82	21.53	17.07
Cashout	32.78	23.02	16.03	24.79	10.27	5.29
Other	3.24	2.55	2.24	4.00	2.08	1.78
Census region						
Midwest	7.88	8.30	8.29	20.18	18.81	15.92
Northeast	29.93	23.69	22.91	19.47	19.78	18.02
South	25.88	22.40	21.11	43.71	38.49	36.83
West	36.31	45.61	47.68	16.63	22.92	29.24
Loan term						
30 years or greater	86.92	87.35	87.53	88.54	87.09	88.36
Less than 30 years	13.08	12.65	12.47	11.46	12.91	11.64
Loan vintage						
Before 2014	60.27	28.14	18.74	76.42	39.00	18.87
2014–16	21.62	38.25	44.27	13.14	27.82	35.68
After 2016	18.11	33.61	36.99	10.44	33.18	45.45

Note: The set of loans presented in this table excludes loans held for sale or accounted for under the fair-value option, loan observations missing data fields used in the model, loans that were in default or had no unpaid balance remaining as of 2018:Q4, loans that were purchased credit-impaired, and other types of loans that are not modeled using the domestic first-lien mortgage model (e.g., commercial loans).

1 The Federal Reserve maps to FICO® Scores as an input to its domestic first-lien mortgage loss model, because these scores are the most widely used commercially available credit scores in the historical data used for estimation.

Table 30 shows the modeled loss rates for the six groups of loans for the DFAST 2019 supervisory severely adverse scenario. Each entry in the table shows the portfolio-level (average) estimated loss rate for the loans in one of the six groups, as well as the median and 25th and 75th percentiles of the estimated loan-level loss rates.

Table 30. Projected first-lien mortgage portfolio loss rates and 25th and 75th percentile ranges by loan and borrower characteristics, 2019:Q1–2021:Q1, DFAST 2019 severely adverse scenario

Loan-to-value at origination	Credit score (FICO® Score)[1]	Loan-level loss rates (percent)			Portfolio-level loss rates (percent)
		25th	Median	75th	Average
80% or less	Under 680	1.3	2.9	5.8	4.1
80% or less	680–739	0.8	1.5	2.7	2.1
80% or less	740 and over	0.2	0.5	0.9	0.8
Greater than 80%	Under 680	3.2	6.7	12.7	10.6
Greater than 80%	680–739	2.4	4.1	6.8	5.3
Greater than 80%	740 and over	0.7	1.4	2.3	1.9

Note: Loan-level loss rates are calculated as cumulative nine-quarter losses on a given loan divided by the unpaid principal balance amount as of 2018:Q4. Portfolio-level loss rates are calculated as the sum of the cumulative nine-quarter losses divided by the sum of the unpaid principal balances as of 2018:Q4. The set of loans presented in this table excludes loans held for sale or accounted for under the fair-value option, loan observations missing data fields used in the model, loans that were in default or had no unpaid balance remaining as of 2018:Q4, loans that were purchased credit-impaired, and other types of loans that are not modeled using the domestic first-lien mortgage model (e.g., commercial loans).

[1] The Federal Reserve maps to FICO® Scores as an input to its domestic first-lien mortgage loss model, because these scores are the most widely used commercially available credit scores in the historical data used for estimation.

Certain groups of loans generally have wider ranges of losses than other groups. Although the loans are grouped according to the most important characteristics in the model, other loan characteristics in the model also affect loss rates, albeit in a more limited manner. Differences in these other characteristics within each loan group are responsible for the range of loss rates shown in the tables. Greater variation in these other characteristics within a group will generally lead to larger ranges of loss rates. For example, the loan-level loss rates shown in table 30 range from 1.3 percent to 12.7 percent for loans with borrower FICO® Scores below 680, a category in which other loan characteristics vary widely. However, loan-level loss rates range from 0.2 percent to 2.3 percent for loans with borrower FICO® Scores above 740, a category in which there is less variation in other loan characteristics.

Portfolios of Hypothetical First-Lien Mortgages and Associated Loss Rates

The effect of loan and borrower characteristics on the losses estimated by the first-lien model can also be illustrated by the differences in the estimated loss rates on specific sets of hypothetical loans. This section contains descriptive statistics from three portfolios of hypothetical loans (table 32) and the modeled loss rates for the three portfolios under the DFAST 2019 supervisory severely adverse scenario (table 33).

The Federal Reserve has designed the portfolios of hypothetical first-lien mortgages to have characteristics similar to the actual loans reported in schedule A.1 of the FR Y-14M. The Federal Reserve provides three portfolios containing 200 loans each, designed to capture characteristics associated with

1. typical set of loans reported in the FR Y-14Q,
2. higher-than-average-risk loans (in this case, loans with LTV at origination of more than 80 percent), and
3. lower-than-average-risk loans (in this case, loans with LTV at origination of 80 percent or lower).

The portfolios of hypothetical loans include 13 variables that describe characteristics of first-lien mortgages that are generally used to estimate first-lien mortgage losses (table 31).[99]

Table 32 contains summary statistics for the portfolios of hypothetical loans in the same format as table 29. The portfolios of hypothetical loans are constructed to capture characteristics of certain sets of loans but are not fully representative of the population of loans reported in table 29. Table 33 contains the loss rates for the portfolios of hypothetical loans calculated under the DFAST 2019 supervisory severely adverse scenario. The portfolio of higher-risk loans has higher loss rates under the severely adverse scenario (loss rate of 4.0 percent) than the portfolio of typical loans (loss rate of 1.4 percent) and the portfolio of lower-risk loans (loss rate of 1.0 percent).

Table 31. List of variables included in portfolios of hypothetical first-lien mortgages

Variable	Mnemonic	Description
Principal balance amount	prin_bal_amt	The principal balance as of 2018:Q4 in dollars
Loan amount at origination	loan_amt_orig	The loan amount at origination in dollars
Loan-to-value ratio at origination	ltv_ratio_orig	The ratio of loan amount at origination to the property value at origination
Credit score at origination	creditbureau_score_orig	The FICO® Scores of the borrower at origination
Property state	prop_state	The state in which the property is located. This includes the 50 U.S. states and the District of Columbia
Occupancy status of property	occupancy_type	The occupancy status of property:
		1 is primary
		2 is second home
		3 is non-owner/investment
		U is unknown
Mortgage product	product	Mortgage products:
		"frm" is fixed-rate mortgage
		"arm" is adjustable-rate mortgage
Property type	prop_type	Property types:
		1 is single
		2 is condo/co-op
		3 is 2–4 units
		4 is other
Mortgage purpose	purpose_type	Mortgage purpose:
		1 is purchase
		2 is rate/term refinance
		3 is cash-out refinance
		4 is other refinance
Loan term at origination	loan_term_orig	Loan term at origination in months
Year of loan origination	year	Year of loan origination
Loan age	loan_age	Loan age in months
Payment status	status	Payment status:
		1 is current (0–89 days past due)
		2 is late (90–180 days past due)

Note: Some of the variables included in the portfolios of hypothetical loans are presented in a more aggregated form than they are reported in the FR Y-14.

[99] The sets of accounts are available for download on the Federal Reserve's website: higher-than-average-risk accounts, https://www.federalreserve.gov/supervisionreg/files/firstlien-high-risk-2020.csv; typical-risk accounts, https://www.federalreserve.gov/supervisionreg/files/firstlien-typical-2020.csv; lower-than-average-risk accounts, https://www.federalreserve.gov/supervisionreg/files/firstlien-low-risk-2020.csv.

Table 32. Summary statistics of selected variables in the portfolios of hypothetical first-lien mortgages
Percent as a share of unpaid principal balance, except as noted

Variables	Higher-risk	Typical	Lower-risk
Current unpaid balance			
$200,000 and Less	9.29	10.73	34.26
$200,001–$400,000	16.80	16.52	29.69
Over $400,000	73.92	72.75	36.05
Payment status			
Current (0–89 days past due)	100.00	99.56	100.00
Late (90–180 days past due)	0.00	0.44	0.00
Occupancy type			
Primary	90.96	88.19	95.42
Second home	7.03	6.05	3.24
Investment	2.01	5.76	1.11
Unknown	0.00	0.00	0.22
Product			
Fixed rate mortgage	63.87	57.69	79.60
Adjustable-rate mortgage	36.13	42.31	20.40
Property type			
Single	82.30	77.84	89.19
Condo/Co-op	14.60	20.61	9.19
2–4 units	2.40	1.33	0.00
Other	0.70	0.23	1.62
Loan purpose			
Purchase	45.37	52.13	71.70
Refinance	34.95	34.03	19.15
Cashout	18.84	12.17	7.46
Other	0.84	1.66	1.69
Census region			
Midwest	11.48	10.51	21.57
Northeast	24.72	26.22	12.28
South	21.43	21.94	44.96
West	42.37	41.32	21.20
Loan term			
30 years or greater	85.71	89.47	82.94
Less than 30 years	14.29	10.53	17.06
Loan vintage			
Before 2014	30.84	34.51	51.50
2014–16	40.37	39.32	30.86
After 2016	28.79	26.17	17.64

Table 33. Projected first-lien mortgage portfolio loss rates, 2019:Q1–2021:Q1, DFAST 2019 severely adverse scenario
Percent

Hypothetical portfolio	Loss rate
Lower-risk	1.0
Typical	1.4
Higher-risk	4.0

Domestic Credit Card Model

Modeled Loss Rates on Pools of Credit Card Accounts

The output of the domestic credit card model is the expected loss on each account. As described above, the Federal Reserve uses the credit card model to project losses on domestic bank cards and domestic charge cards, and estimated credit card loss rates depend on a number of variables. This section groups domestic bank card accounts (credit card accounts) according to their commercially available credit score, which is one of the most important variables in the model. FICO® Scores are the most widely used commercially available credit scores in the historical data used to estimate the model.[100] Credit card accounts reported on schedule D.1 of the FR Y-14M report as of the fourth quarter of 2018 are segmented by FICO® Score into four groups of accounts:[101]

1. Accounts with FICO® Score under 650
2. Accounts with FICO® Score from 650 to 699
3. Accounts with FICO® Score from 700 to 749
4. Accounts with FICO® Score above 750

The remainder of this section reports summary statistics and modeled loss rates for these four groups of credit card accounts.

Table 34 reports summary statistics for the four groups of credit card accounts. The summary statistics cover a wide set of variables that capture important account characteristics.

Table 34. Summary statistics of selected variables in the credit card data by credit score
Percent as a share of cycle ending balance, except as noted

Variables	Credit score (FICO® Score)[1]			
	Under 650	650 to 699	700 to 749	750 and over
Number of accounts (millions)	42.98	34.86	34.59	69.25
Credit card type				
General purpose	88.90	92.14	93.67	93.98
Private label	11.10	7.86	6.33	6.02
Current credit limit				
$1,500 and less	16.33	4.70	1.60	0.62
$1,501–$7,500	54.98	44.37	26.95	13.89
Over $7,500	28.69	50.93	71.44	85.49
Days past due				
Current	82.34	98.37	99.28	99.69
30+ Days past due	17.66	1.63	0.72	0.31

(continued)

[100] FR Y-14 reporters are not required to report a particular credit score. For the purposes of making projections using a model estimated with FICO® Scores, the Federal Reserve maps scores reported on the FR Y-14 to FICO® Scores.

[101] The set of accounts presented in this table excludes accounts held for sale or accounted for under the fair-value option, observations missing data fields used in the model, accounts with 0–1 percent utilization rate as of 2018:Q4, and other types of accounts that are not modeled using the credit card model.

Table 34.—*continued*

Variables	Credit score (FICO® Score)[1]			
	Under 650	650 to 699	700 to 749	750 and over
Product type				
Co-brand	19.55	21.94	22.18	29.68
Other	80.45	78.06	77.82	70.32
Month-end account status				
Open and active	91.31	99.55	99.84	99.94
Other	8.69	0.45	0.16	0.06
Account origination year				
2014 and prior	43.33	48.77	54.37	53.55
2015	14.30	11.66	9.61	8.66
2016	16.25	13.26	10.92	10.99
2017	15.17	13.57	12.06	12.52
2018	10.94	12.74	13.04	14.29
Month-end close status				
Not closed	91.28	99.56	99.84	99.95
Closed	8.72	0.44	0.16	0.05
Cycle ending balance				
Under $1,000	11.75	5.09	4.03	8.70
$1,000–$1,999	13.79	8.83	6.52	11.08
$2,000–$2,999	13.66	9.92	7.42	10.55
$3,000–$4,999	19.82	18.75	15.37	17.88
$5,000–$9,999	24.36	30.56	30.31	27.45
$10,000 and over	16.61	26.85	36.35	24.34
Income at origination				
$50,000 and less	45.04	38.09	33.55	24.98
$50,001–$100,000	36.77	38.13	38.14	36.99
Over $100,000	18.19	23.79	28.32	38.03
Original credit limit				
$1,500 and less	35.00	19.53	11.20	4.71
$1,501–$7,500	47.49	51.89	46.38	31.61
Over $7,500	17.51	28.58	42.42	63.68
Interest rate at cycle end				
Under 12%	7.72	9.51	11.92	11.83
12%–14.99%	4.07	6.61	11.32	15.65
15%–19.99%	21.11	29.43	37.48	51.65
20%–23.99%	17.52	20.06	18.63	11.10
24% and over	49.58	34.39	20.65	9.77

Note: The set of consumer bank card accounts presented in this table excludes accounts held for sale or accounted for under the fair-value option, observations missing data fields used in the model, accounts with 0–1 percent utilization rate as of 2018:Q4, and other types of accounts that are not modeled using the domestic credit card model.

[1] The Federal Reserve maps to FICO® Scores as an input to its credit card loss model, because these scores are the most widely used commercially available credit scores in the historical data used for estimation.

Table 35 shows the modeled loss rates for the four groups of accounts under the DFAST 2019 supervisory severely adverse scenario. Each entry in the table shows the portfolio-level (average) estimated loss rate for the accounts in one of the four groups, as well as the median and 25th and 75th percentiles of the estimated account-level loss rates.

Table 35. Projected credit card portfolio loss rates and 25th and 75th percentile ranges by credit score, 2019:Q1–2021:Q1, DFAST 2019 severely adverse scenario

Credit score (FICO® Score)[1]	Account-level loss rates (percent)			Portfolio-level loss rates (percent)
	25th	Median	75th	Average
Under 650	29.8	41.0	64.3	41.5
650–699	15.9	20.5	29.6	20.1
700–749	4.9	11.6	19.1	10.5
750 and over	4.3	6.5	13.8	5.5

Note: Account-level loss rates are calculated as cumulative nine-quarter losses on a given account divided by initial utilized balance. Portfolio-level loss rates are calculated as the sum of the cumulative nine-quarter losses divided by the sum of initial utilized balances. The set of consumer bank card accounts on which loss rates are calculated excludes accounts held for sale or accounted for under the fair-value option, observations missing data fields used in the model, accounts with 0–1 percent utilization rates as of 2018:Q4, and other types of accounts that are not modeled using the domestic credit card model.

[1] The Federal Reserve maps to FICO® Scores as an input to its credit card loss model, because these scores are the most widely used commercially available credit scores in the historical data used for estimation.

Certain groups of accounts generally have wider ranges of losses than other groups. Although accounts are grouped according to one of the most important characteristics in the model, other account characteristics in the model also affect loss rates, albeit in a more limited manner. Differences in these other characteristics within each account group are responsible for the range of loss rates shown in the tables. Greater variation in these other characteristics within a group will generally lead to larger ranges of loss rates. For example, the account-level loss rates shown in table 35 range from 29.8 percent to 64.3 percent for accounts with FICO® Scores below 650, a category in which other account characteristics vary widely. However, account-level loss rates range from 4.3 percent to 13.8 percent for accounts with FICO® Scores above 750, a category in which there is less variation in other account characteristics.

Portfolios of Hypothetical Credit Card Accounts and Associated Loss Rates

The effect of account characteristics on the losses estimated by the credit card loss model can also be illustrated by the differences in the estimated loss rates on specific sets of hypothetical accounts. This section contains descriptive statistics for three portfolios of hypothetical accounts (table 37) and the modeled loss rates for the three portfolios under the DFAST 2019 supervisory severely adverse scenario (table 38).

The Federal Reserve has designed the portfolios of hypothetical accounts to have characteristics similar to the actual accounts reported in schedule D.1 of the FR Y-14M. The Federal Reserve provides three portfolios containing 200 accounts each, designed to capture characteristics associated with

1. typical set of accounts reported in the FR Y-14M,
2. higher-than-average-risk accounts (in this case, accounts with FICO® Scores under 700),
3. lower-than-average-risk accounts (in this case, accounts with FICO® Scores 700 and greater).

The portfolios of hypothetical accounts include 12 variables that describe characteristics of credit card accounts that are generally used to estimate credit card losses (table 36).[102]

Table 36. List of variables included in portfolios of hypothetical credit card accounts

Variable	Mnemonic	Description
Credit card type	creditcardtype	Credit card type: 1 is general purpose 2 is private label
Current credit limit	currentcreditlimit	Maximum dollar amount that may be borrowed on the account during the reporting month, as of month's end
Days past due	dayspastdue	Actual number of days the account is past due as of the current reporting month's cycle date
Product type	producttype	Product type: 1 is co-brand 2 is other
Month-end account status	activeflag	Whether the account has had any debit, credit, or balance activity in the last 12 months at month end: 0 is open and active 1 is other
Account origination year	accountoriginationyear	Year in which the original credit card was issued
Month-end close status	monthendclosedrevokedflag	Whether, in the current reporting month, the account is closed or revoked and has no further charging privileges: 0 is not closed 1 is closed
Refreshed credit score (FICO® Scores)[1]	refreshedcreditscoreprimaryborrower	The most recently updated credit score available for the primary account holder at origination using a commercially available credit bureau score
Cycle ending balance	cycleendingbalance	Total outstanding balance for the account at the end of the current month's cycle
Income at origination	borrowerincome	Borrower's income
Original credit limit	originalcreditlimit	Original credit limit
Interest rate at cycle end	cycleendingretailapr	Purchase APR

[1] The Federal Reserve maps to FICO® Scores as an input to its credit card loss model because these scores are the most widely used commercially available credit scores in the historical data used for estimation.

Table 37 contains summary statistics for the portfolios of hypothetical credit card accounts in the same format as table 34. The portfolios of hypothetical accounts are constructed to capture characteristics of certain sets of accounts but are not fully representative of the population of accounts reported in table 34. Table 38 contains the loss rates for the portfolios of hypothetical credit card accounts calculated under the DFAST 2019 supervisory severely adverse scenario. The portfolio of higher-risk accounts has higher loss rates under the severely adverse scenario (loss rate of 28.9 percent) than the portfolio of typical accounts (loss rate of 18.8 percent) and the portfolio of lower-risk accounts (loss rate of 7.7 percent).

[102] The sets of accounts are available for download on the Federal Reserve's website: higher-than-average-risk accounts, https://www.federalreserve.gov/supervisionreg/files/cards-high-risk-2020.csv; typical-risk accounts, https://www.federalreserve.gov/supervisionreg/files/cards-typical-2020.csv; lower-than-average-risk accounts, https://www.federalreserve.gov/supervisionreg/files/cards-low-risk-2020.csv.

Table 37. Summary statistics of selected variables in the portfolios of hypothetical credit card accounts
Percent as a share of cycle ending balance, except as noted

Variables	Lower-risk	Typical	Higher-risk
Credit card type			
General purpose	97.68	93.74	86.55
Private label	2.32	6.26	13.45
Current credit limit			
$1,500 and less	1.98	4.08	15.66
$1,501–$7,500	23.49	53.53	65.40
Over $7,500	74.53	42.39	18.94
Days past due			
Current	100.00	96.21	94.98
30+ Days past due	0.00	3.79	5.02
Product type			
Co-brand	23.18	8.87	16.74
Other	76.82	91.13	83.26
Month-end account status			
Open and active	100.00	100.00	98.60
Other	0.00	0.00	1.40
Account origination year			
2014 and prior	58.42	59.06	43.89
2015	6.33	7.18	19.03
2016	11.80	12.08	9.42
2017	15.57	8.18	16.49
2018	7.88	13.50	11.17
Month-end close status			
Not closed	100.00	100.00	98.60
Closed	0.00	0.00	1.40
Cycle ending balance			
Under $1,000	5.53	7.82	7.46
$1,000–$1,999	9.52	8.83	14.91
$2,000–$2,999	9.24	13.86	20.76
$3,000–$4,999	15.89	16.82	22.74
$5,000–$9,999	30.21	21.37	24.91
$10,000 and over	29.61	31.30	9.23
Income at origination			
$50,000 and less	47.58	50.26	46.83
$50,001–$100,000	16.65	18.93	24.25
Over $100,000	35.77	30.81	28.92
Original credit limit			
$1,500 and less	7.94	26.52	47.74
$1,501–$7,500	55.82	39.89	47.67
Over $7,500	36.24	33.60	4.59
Interest rate at cycle end			
Under 12%	26.05	41.36	17.06
12%–14.99%	15.31	26.44	13.70
15%–19.99%	25.52	17.12	23.79
20%–23.99%	20.47	6.58	20.52
24% and over	12.65	8.49	24.94

Table 38. Projected credit card portfolio loss rates, 2019:Q1–2021:Q1, DFAST 2019 severely adverse scenario
Percent

Hypothetical portfolio	Loss rate
Lower-risk	7.7
Typical	18.8
Higher-risk	28.9

Note: Portfolio-level loss rates are calculated as the sum of the cumulative nine-quarter losses divided by the sum of initial utilized balances.

Explanatory Notes on Model Disclosures

The model disclosures in this document focus on the design of and projections from specific models, whereas the disclosures of supervisory stress test results include projections aggregated to the portfolio level. In most cases, those portfolio-level aggregates contain outputs from multiple supervisory models.[103] As such, the results shown in the two different disclosures will be different.

This document includes disclosures of loss rates on loan and account segments and on hypothetical portfolios of loans and accounts. These loss rates differ from those included in the stress test results disclosures in that they do not include accounting and other adjustments used to translate projected credit losses into net income. In the supervisory stress test results disclosure, the Federal Reserve makes certain accounting adjustments to translate supervisory model estimates into provisions and other income or expense items needed to calculate stressed pre-tax net income. These adjustments often depend on factors that vary across participating firms, such as write-down amounts on accounts purchased with credit impairments.

[103] See Board of Governors of the Federal Reserve System, "Mapping of Loan Categories to Disclosure Categories," *Dodd-Frank Act Stress Test 2019: Supervisory Stress Test Results* (Washington: Board of Governors, June 2019), 47, https://www.federalreserve.gov/publications/files/2019-dfast-results-20190621.pdf.

Appendix A: Model Changes for the 2020 Supervisory Stress Test

Each year, the Federal Reserve has refined both the substance and process of the supervisory stress test, including its development and enhancement of independent supervisory models. The supervisory stress test models may be enhanced to reflect advances in modeling techniques; enhancements in response to model validation findings; incorporation of richer and more detailed data; and identification of more stable models or models with improved performance, particularly under stressful economic conditions.

For the 2020 supervisory stress test, the Federal Reserve aligned the calculation of regulatory capital ratios and balances with recent changes in regulations; enhanced the models that project certain components of pre-provision net revenue (PPNR), credit card losses, and corporate loan losses; completed a phase-in for the auto loan model; and modified the trading and private equity model. In addition to these model changes, the Federal Reserve made less material enhancements to simplify models and account for changes in the historical data used to estimate the models.[104]

Alignments to Changes in Regulatory Capital Rules

The Federal Reserve modified the capital calculation to align the computations with the capital simplification, tailoring, and stress capital buffer rules.[105] To conform the calculations to the simplifications rule, the Federal Reserve increased in its capital calculation the threshold for deducting mortgage servicing assets, certain deferred tax assets (DTAs) arising from temporary differences, and investments in the capital of unconsolidated financial institutions from regulatory capital. Similarly, to align with the tailoring rule, the Federal Reserve will no longer include accumulated other comprehensive income in the calculation of certain firms' regulatory capital. Consistent with the stress capital buffer rule, the Federal Reserve will no longer include certain capital actions or the impacts of material business plan changes in its regulatory capital calculation and will assume that a firm's balances, RWAs, and leverage ratio denominators generally remain unchanged over the projection horizon.[106] In addition, to maintain a consistent capital calculation methodology across all firms, the Federal Reserve will limit the use of firms' projections in the capital calculation.

The Federal Reserve will continue to monitor changes to laws and regulations related to the pandemic response and could make additional changes to its calculations if appropriate.

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[104] Portfolios with material model changes are defined as those in which the change in revenue or losses exceeds 50 basis points for any firm individually under the severely adverse scenario, expressed as a percentage of risk-weighted assets (RWAs), based on data and scenarios from the 2019 supervisory stress test. In cases in which a portfolio contains more than one change, materiality is defined by the net change.

[105] See note 90.

[106] In projecting a firm's RWAs and leverage ratio denominators, the Federal Reserve will account for the effect of changes associated with the calculation of regulatory capital or changes to the Board's regulations.

Refinements to Supervisory Models

PPNR Models

The Federal Reserve made two enhancements to the PPNR autoregressive models, which are the models used to project most PPNR components. In prior versions of the models, the Federal Reserve estimated firm fixed effects using the full set of data available since the financial crisis and included in each model one or more lags of the quarterly observations of the respective PPNR component. The enhanced versions estimate firm fixed effects using data from the more recent past (a trailing multiyear fixed effect) and include the lag of the respective PPNR component measured as the average of that component over the prior year. These enhancements increase the importance of firm performance in more recent years and diminish the degree to which quarterly volatility in historical PPNR affects projections over the horizon.

In addition, the Federal Reserve re-estimated its full suite of PPNR models on an expanded sample, re-specifying models based on performance testing. While those re-specifications have a small effect on overall PPNR, they result in larger offsetting effects on the projections of individual components. For example, the effect of model enhancements on projections of noninterest income is offset, in part, by the effect on the projections of noninterest expenses. Overall, the changes improve model performance for total PPNR.

These refinements have material effects on projections for certain firms.[107] Consistent with the Federal Reserve's stated policy for material model changes, the PPNR estimates for the 2020 supervisory stress test will be the average of the model used in 2019 and the updated model.[108] PPNR estimates for the 2021 supervisory stress test will only reflect the updated model.

Credit Card Model

The Federal Reserve refined the credit card model by applying an adjustment to card losses for firms with credit card revenue and loss sharing agreements (RLSAs). In these agreements, a portion of the revenues and losses generated by a specified credit card portfolio may be shared with a private entity. The previous version of the credit card model did not fully account for RLSAs. These agreements were reflected only in supervisory projections of the firm's PPNR to the extent that firms reported historical PPNR net of these agreements. In cases for which revenues but not losses on RLSAs are reported in historical PPNR, the updated credit card model adjusts losses to reflect the portion shared with the private entity. This update increases consistency in the treatment across firms with RLSAs. The Federal Reserve also re-estimated the credit card model using additional data to better capture recent trends. The collective impact is expected to result in a slight increase in overall losses pro-

[107] Analysis was conducted using data and scenarios from the 2019 supervisory stress test. The effect on projections for the 2020 supervisory stress test and future tests is uncertain and will depend on changes in firm portfolios, data, and scenarios.

[108] Starting in DFAST 2017, the Federal Reserve began to adhere to a policy of phasing in the most material model enhancements over two stress test cycles to smooth the effect on post-stress capital ratios. See Stress Testing Policy Statement, 82 Fed. Reg. 59528 (Dec. 15, 2017).

jected by the domestic credit card model, with larger increases for firms with material bank card exposures.[109]

Corporate Loan Model

The Federal Reserve modified the corporate model to separately calibrate financial and nonfinancial obligors. This modification reflects updated expected default frequency (EDF) data that has broader coverage and an extended sample period. The Federal Reserve also re-estimated the corporate model using this extended sample to better capture the effects of the financial crisis. The collective impact is expected to result in a slight decrease in overall losses projected by the corporate model, mainly due to lower loss rates on financial obligors, with no material impacts on any firm.[110]

Other Model Changes

Phase-in of the Auto Loan Model

The Federal Reserve began a two-year transition to an updated auto loan model in the 2019 supervisory stress test, with the updated model fully in effect for 2020. The two-year phase-in policy was employed because the auto model refinements materially affected the forecast auto loan losses for a number of firms.[111] The 2019 changes to the auto loan model are described in the 2019 document on the supervisory stress test methodology.[112] Collectively, the enhancements are expected to result in a small increase in overall projected auto loan losses; however, for firms with large domestic auto loan portfolios, the changes may result in materially higher projected losses.[113]

Trading and Private Equity Model

The Federal Reserve will modify the estimate of losses on private equity investments in affordable housing that qualify as Public Welfare Investments (PWI) under Regulation Y. These investments will be separately identified and losses will be calculated using the market shock that is applied to Section 42 Housing Credits. The Federal Reserve intends to collect additional information to refine its approach to identifying these investments and estimating their losses.

Minor Refinements and Re-estimation

Each year, the Federal Reserve makes a number of relatively minor refinements to models that may include re-estimation with new data, re-specification based on performance testing, and other refinements to the code used to produce supervisory projections. In 2019, the Federal Reserve made such refinements to the models for commercial real estate, counterparty,

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[109] See note 107.

[110] See note 107.

[111] See note 108.

[112] See Board of Governors of the Federal Reserve System, *Dodd-Frank Act Stress Test 2019: Supervisory Stress Test Methodology* (Washington: Board of Governors, March 2019), https://www.federalreserve.gov/publications/files/2019-march-supervisory-stress-test-methodology.pdf.

[113] See note 107.

fair value for debt and equity securities, first- and second-lien mortgages, and operational risk. The refinements collectively resulted in a minimal change in post-stress capital ratios with no material impacts on any disclosed firm.[114]

[114]See note 107.

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