Board of Governors of the Federal Reserve System
Washington, DC 20551

Supervisory Stress Test Model Documentation

Operational Risk Model

October 2025

This document summarizes the Operational Risk Model that the Board of Governors of the Federal Reserve System (Board) intends to use in the 2026 Supervisory Stress Test. The following sections provide a summary of the model, model components, and alternatives considered, along with other model-specific details. Documentation on the other models that the Board intends to use in the 2026 Supervisory Stress Test is available at the following link: https://www.federalreserve.gov/supervisionreg/dfa-stress-tests-2026.htm.

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A. Operational Risk Model

i. Statement of Purpose

The Board is proposing to implement two changes to the operational-risk loss model for the 2026 stress test. First, the Board is proposing to discontinue using a macroeconomic regression model to project operational losses. Currently, operational loss projections are primarily the average of the output of a macroeconomic regression and a loss distributional model. Beginning in the 2026 stress test, the Board proposes to primarily use the distributional model to produce operational loss projections. Discontinuing the macroeconomic regression is discussed further in Section A.vi.a. Second, the Board proposes to subtract several highly liquid assets from total assets for purposes of scaling historical operational losses. Removing highly liquid assets is discussed further in Section A.vii. The Board seeks public input on these proposed changes to the model.

The two proposed model changes would better align with the Board's stress testing principles of stability, robustness, consistency, and comparability. In particular, the macroeconomic regression was determined to perform inconsistently across different recessionary periods in the estimation sample and was further determined to be highly sensitive to assumptions around the timing of large historical loss events. The distributional model, by contrast, is less sensitive to the timing and impact of large loss events. Further, operational loss projections depend on total assets, which are used to scale historical losses. Certain sub-components of total assets can be volatile, which has translated into volatile loss projections. Subtracting highly liquid instruments, such as cash equivalents and government securities, from total assets yields a model that would have produced more stable loss projections over recent cycles.

The operational-risk loss model (Operational Risk Model) is a component model that estimates potential operational losses over the hypothetical stress scenario. Operational risk is a noninterest expense component of pre-provision net revenue. As operational losses tend to exhibit distinct characteristics—such as a heavy-tailed distribution—they are estimated separately from other components of pre-provision net revenue.[1]

Operational losses include losses stemming from events such as fraud; computer system failures; process errors; and lawsuits by employees, customers, or other parties.[2] Operational losses are large and pervasive in the banking sector. According to supervisory data, firms subject to the Board's stress test experienced nearly $450 billion in realized operational losses between 2000 and 2023. Many of these losses originated from the 2008 financial crisis. For instance, five of the largest U.S. banking organizations arrived at a $26 billion settlement related to foreclosure abuses during the 2008 financial crisis (Schwartz and Dewan, 2012).[3] Separately, many large banking organizations took sizable losses by repurchasing troubled mortgages from Fannie Mae and Freddie Mac (Protess and Dash, 2011).[4]

Projected operational losses from the stress test contribute to firms' regulatory capital requirements, which are designed to ensure that the banking sector is well-positioned to withstand hypothetical adverse events. The 2008 financial crisis is a concrete example of an economic crisis that is associated with heightened operational risks and highlights the importance of accounting

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[1] Because of the distinct characteristics of operational-risk losses, a set of modeling approaches evolved over time for this specific risk area. For an introductory overview of the characteristics of operational loss distributions and approaches to modeling operational risk, *see* Lewis, N.D.C., 2004. *Operational Risk: Applied Statistical Methods for Risk Management*. John Wiley & Sons.

[2] *See* Basel Committee on Banking Supervision (BCBS), 2024. International Convergence of Capital Measurement and Capital Standards: A Revised Framework. https://www.bis.org/publ/bcbs107.pdf.

[3] *See* Schwartz, N.D., and Dewan, S. (Feb. 9, 2012). *States Negotiate $26 Billion Agreement for Homeowners*. New York Times. http://www.nytimes.com/2012/02/09/business/states-negotiate-25-billion-deal-for-homeowners.html.

[4] Mortgages repurchased from government sponsored enterprises during and following the 2008 financial crisis were often accompanied by claims that lenders misrepresented the quality of these mortgages. As such, losses associated with these repurchases are considered operational losses, rather than credit losses. *See* Protess, B., and Dash, E. (Jan. 3, 2011). *Bank of America Buys Back $2.5 Billion in Mortgage Debt*. New York Times. https://archive.nytimes.com/dealbook.nytimes.com/2011/01/03/fannie-and-freddie-continue-to-collect-on-bad-loans/.

for potential operational losses in a hypothetical stress scenario. In addition to operational losses associated with the 2008 financial crisis, firms have experienced large operational loss events that affected several firms or specific to individual firms. While some of these loss events are not associated with macroeconomic shocks, they potentially may occur during stressful periods. Therefore, the Operational Risk Model stress tests firms to operational risk comprehensively and produces stressful operational losses that could be systemic for many firms, correlated in several firms, or specific to individual firms. The Operational Risk Model is designed to project quarterly losses over the projection horizon for each supervisory stress test scenario. Key firm characteristics that affect projected losses include the size of the firm measured by total assets and the firm's historical operational losses by operational-risk loss category.

ii. Model Overview

Operational loss projections are primarily produced by a distributional model[5] that uses a historical simulation to create an unconditional distribution of operational loss amounts.[6] An unconditional distribution is one that is not restricted by or contingent on firm-specific characteristics or environmental factors. Projections are based on a selected tail percentile of the distribution which is informed by the frequency of historical recessions. An additional model component generates projections for smaller losses that are excluded from the distributional model.

The distributional model and the small-loss component both produce single 9-quarter loss projections for each firm, which the Board then allocates evenly over the stressed projection horizon. Final operational loss projections for each firm and each quarter of the projection horizon

[5] A "distributional model" is a generic name for a class of models or a framework describing how economic values or outcomes are distributed across units of observations within a population.

[6] In addition to the distributional model, the Board used a macroeconomic regression model to project operational losses through the 2025 stress test cycle. The Board proposes to discontinue using the macroeconomic regression model starting with the 2026 Stress Test.

are the sum of the projections produced by the distributional model and the small-loss component model.

a. Overview of Distributional Model

The Board has determined that the use of a distributional model is appropriate given the properties and characteristics of operational losses, which have a wide range of causes and can be influenced by many different economic and non-economic factors. For example, the widespread system outages caused by a faulty CrowdStrike update in 2024 is an example of an operational event caused by non-economic factors that was felt concurrently by firms across the country (Rothenberg, 2024).[7] As the distributional model is driven by the unconditional properties of the historical operational loss event distribution—that is, properties that are not contingent on any specific risk factors—the model's loss projections reflect a severe and rare outcome that could result from a broad range of different loss events. As discussed in Section A.v, the Board has determined that a distributional model is appropriate given the idiosyncratic nature of operational risk and the ability of the distributional approach to capture loss events with a wide range of underlying causes. The Board further believes the distributional model best accounts for large loss events that might arise from a number of different factors, and which may coincide with a severe macroeconomic downturn.

b. Overview of Small-Loss Component Model

In addition to the distributional model, the Board uses a small-loss model component to project loss events of less than $20,000. Firms have different operational loss collection and

[7] The CrowdStrike incident created transactions processing problems at some financial firms. *See* Rothenberg, E. (Jul. 20, 2024). *Timeline: How the CrowdStrike outage unfolded*. CNN. https://edition.cnn.com/2024/07/20/tech/timeline-crowdstrike-system-outage/index.html; Saeedy, A. (Jul. 19, 2024). *Banks Grapple with Technical Difficulties Following CrowdStrike Outage*. Wall Street Journal. https://www.wsj.com/livecoverage/stock-market-today-dow-sp500-nasdaq-live-07-19-2024/card/banks-grapple-with-technical-difficulties-following-crowdstrike-outage-ZQAy4mQ7okOmCkam0CIY?.

reporting thresholds. To treat all firms consistently, the Federal Reserve excludes loss events of less than $20,000 from the distributional model and projects these losses using a separate model component. Losses projected from this separate component are then added to the projections from the distributional model to produce final operational loss projections.

c. Application of the Federal Reserve's Principles

The Operational Risk Model is consistent with the Board's policies and procedures that guide stress testing model development, as outlined in the Stress Testing Policy Statement.[8]

One supervisory modeling policy of particular importance for operational risk is the emphasis on an industry-level approach[9] and the calibration of parameters using data from many institutions.[10] Given the idiosyncratic nature of operational risk, a firm's loss history may not fully capture the firm's susceptibility to future operational risks. Throughout the modeling suite, parameters are informed by industry experience rather than exclusively firm-specific historical experience. By employing an industry-level approach, the model assumes that operational losses experienced by some firms could be applicable to other institutions in the future. The emphasis on industry-level parameter estimation is consistent with the modeling principles of comparability of results and limiting reliance on individual firms' past outcomes, as a firm's projections depend heavily on industry data. Using an industry-focused model also promotes stability and robustness—two key modeling objectives—as parameters are estimated on a large dataset that is generally stable from cycle to cycle.

Further, though model parameters are estimated on historical data, using a simulation limits the reliance of loss projections on past outcomes. The simulated distribution is the product of

[8] For the full statement, *see* 12 CFR 252, Appendix B.

[9] Throughout this section, the term "industry" is used to refer to the set of covered firms subject to the stress test.

[10] *See* 12 CFR 252, Appendix B, part 2.4(d).

250,000 random draws from loss frequency and severity distributions. As such, the aggregate distribution reflects a range of plausible loss realizations, not just those with historical precedent.[11]

Each component of the operational risk modeling suite is discussed in detail below.

iii. Data Sources

The Operational Risk Model primarily uses two types of data: historical operational loss data from the FR Y-14Q, Schedule E.1 and firm asset size data sourced primarily from the FR Y-9C.

a. FR Y-14Q Data

All firms subject to the Federal Reserve's stress test are required to report a complete history of their operational loss events. Firms submit their historical individual loss events quarterly on Schedule E.1 of the FR Y-14Q reporting form. As operational loss events have a wide range of causes, the reporting form requires firms to sort operational losses into seven standard categories consistent with the loss categories defined by the Basel Committee on Banking Supervision (BCBS). **Table A1** below shows the percentage of total reported operational loss amounts by these Basel event types.[12]

[11] While the distributional model is based on historical data, the model is not constrained by historical precedent. For instance, it has the ability to produce simulated nine-quarter loss projections that are larger than the firm's historical maximum nine-quarter loss amount.

[12] The Basel Event Type refers to the Level 1 Basel Event-Type Category reported on Field Reference J of the Schedule E.1 of the FR Y-14Q reporting form. Throughout the remainder of this section, the variable will be referred to simply as an event type.

Table A1 - Percentage of Total Reported Gross Operational Losses by Event Type

Event Type	% of Total Losses
Clients, Products, and Business Practices (CPBP)	72.5
Execution, Delivery, and Process Management (EDPM)	14.8
External Fraud (EF)	4.9
Employment Practices and Worker Safety (EPWS)	3.0
Internal Fraud (IF)	2.3
Business Disruption and System Failures (BDSF)	1.3
Damage to Physical Assets (DPA)	1.2

Note: This table shows the proportion of gross operational losses by event type incurred between 2000 and 2022 by firms subject to the 2024 stress test.

As explained below in Section A.iv, each event type category is modeled separately in the distributional model. The separate treatment reflects different distributional properties for each event type. For instance, loss events related to fraud would be expected to have a different frequency from legal events. The event type with the largest share of industry-aggregate operational losses is Clients, Products, and Business Practices. Firms often categorize legal events in this event type, particularly those related to improperly marketed products that were prevalent during the 2008 financial crisis.

Other key fields in the FR Y-14Q reporting form used throughout the model suite are the Gross Loss Amount and the Accounting Date (the date a given loss event was reflected in the firm's financial statements). Often, when a loss event unfolds over time, firms will report different accounting dates for different loss impacts.[13] In such situations, the Board assumes that the full financial impact of a loss event is realized within the first quarter in which a loss impact was reported. As firms have different loss collection and reporting standards, this assumption allows

[13] The term "impact" refers to a portion of an operational loss event. For instance, a lawsuit might constitute a single operational loss event, but it may involve several distinct loss impacts that occur at different points in time, such as the settlement or payments to outside counsel.

for interpretability and consistency across firms. The assumption is discussed further in Section A.vii.

For a small share of operational loss events, firms recover a portion of the loss amount. In these cases, firms separately report the gross loss amount and recovered amounts. Given the lower chance of recovery during stressful periods,[14] and the uncertainty over when recoveries will materialize, the Operational Risk Model conservatively estimates losses using the gross loss amount rather than losses net of recoveries.

b. FR Y-9C Data

The Operational Risk Model uses firm asset size to normalize operational losses across firms and over time. Asset size is primarily measured by total assets as reported on the FR Y-9C reporting form.[15] When FR Y-9C data are unavailable for a firm,[16] the Federal Reserve will source data from either the Reports of Condition and Income (Call Reports), the OTS 1313 reporting form, or financial statements sourced from a third party data vendor. Scaling historical loss events by asset size is discussed further in Section A.vii.

iv. Model Specification

As described above, the Operational Loss Model primarily produces operational loss projections with a distributional model that uses a historical simulation to create an unconditional distribution of operational losses. The operational risk modeling suite also includes an additional component to generate projections for small loss events excluded from the distributional model.

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[14] *See* Frame, W.S., et al., 2024. Operational loss recoveries and the macroeconomic environment: Evidence from the U.S. banking sector. *Journal of Banking & Finance*, 107220. The authors show that recoveries diminish during periods of stress.

[15] Total Assets is reported on Schedule HC, line 12 of the FR Y-9C reporting form.

[16] Data may be unavailable during historical periods when the covered entity was not required to report the FR Y-9C.

The distributional model uses a historical simulation that produces a nine-quarter aggregate loss distribution. Projections under the severely adverse scenario are based on a tail percentile of that distribution. As discussed above and in more detail in Section A.v, the distributional model is appropriate given the idiosyncratic nature of operational risk and wide range of causes that underlie operational losses.

The model simulates a nine-quarter loss distribution by modeling loss event severity and frequency separately and combining them through a Monte Carlo simulation. Loss event severity defines how large a given operational loss event might be. Loss event frequency defines how many times individual loss events might occur in a given period of time.

The body and tail of the loss event severity distribution are defined based on the distribution across all covered firms of the ratio of historical loss event amounts scaled by historical firm asset size. The body-tail cutoff point is set at the 99th percentile of the entire loss-to-assets distribution for each event type. Tail losses have a loss-to-assets ratio equal to or greater than the body-tail cutoff point, and body losses have a loss-to-assets ratio less than the body-tail cutoff point. As detailed below, projected losses from the body and tail of the loss event severity distribution are modeled differently and separately.

a. Tail Loss Event Modeling

The Board uses a simulation-based approach to model projected losses from the tail of the loss event severity distribution. This simulation model follows a common approach in operational risk modeling known as the Loss Distribution Approach (LDA).[17] In this application, the approach

[17] LDA models are commonly used in actuarial science. For an overview and applications to the insurance industry, *see* Klugman, P., et al. (1998). *Loss Models: From Data to Decision*. Wiley-Interscience.

models tail loss frequency and tail loss severity separately and combines them to produce an unconditional aggregate loss distribution. The process has two steps:

- First, calculate a firm-specific parameter representing the frequency of tail loss events for each firm j and event type *e*.
- Second, use a Monte Carlo simulation to select random draws from the pool of tail loss ratios for event *e* (those in the top 1% of the industry loss severity distribution) and create an aggregate 9-quarter loss distribution.

(1) Step 1: Tail Frequency Parameter

The initial step in this model is the calculation of a parameter for each firm and event type that represents the frequency of tail loss events over a 9-quarter horizon. This parameter is, for each event type, the simple average of a firm-specific parameter and, given the stress test modeling principles' emphasis on industry-level modeling, an industry-specific parameter. The firm-specific tail frequency parameter λ for firm j and event type *e* is calculated as:

Equation A1 – Firm-Specific Tail Frequency Parameter

$$\lambda_{j,e}^{individual} = \frac{\#Tail\ Events_{j,e}}{\#Quarters_{j,e}} \times 9$$

where $\#Tail\ Events_{j,e}$ is the number of historical tail loss events for firm j within event type *e*, and $\#Quarters_{j,e}$ is the number of quarters of historical operational loss data available for firm j within event type *e*.

The industry-specific tail frequency parameter for each firm j and event type *e* is calculated as:

Equation A2 – Industry-Specific Tail Frequency Parameter

$$\lambda_{j,e}^{industry} = \frac{ln\left(TotalAssets_{j,t=0}\right)}{\sum_j ln\ \left(TotalAssets_{j,t=0}\right)} \times \sum_{j,e} \lambda_{j,e}^{individual}$$

where $TotalAssets_{j,t=0}$ are the total assets of firm j as of the quarter prior to the first quarter of the projection horizon of the stress testing exercise. The intent of the industry-specific tail frequency parameter is to sum individual tail parameters ($\lambda_{j,e}^{individual}$) across all firms for a given event type and then apply a weight for firm *j* according to its relative asset size. In applying a weight based on asset size, the Board takes the natural logarithm of total assets in the numerator and denominator because the Board has observed that tail loss frequency is concave in asset size.

The tail loss event frequency parameter for each firm and event type used in the Monte Carlo simulation is the average of the firm-level frequency parameter and the industry parameter:

Equation A3 – Tail Loss Event Frequency Parameter

$$\lambda_{j,e}^{tail} = \frac{\lambda_{j,e}^{individual} + \lambda_{j,e}^{industry}}{2}$$

(2) Step 2: Monte Carlo Simulation

The next step in this model is to run a Monte Carlo simulation to produce an aggregate nine-quarter loss distribution. The simulation follows the steps below for each firm *j* and event type *e*:

1. Randomly draw from a Poisson distribution with expected value $\lambda_{j,e}^{tail}$. The drawn value is denoted as *m*.
2. Make *m* random draws from the pool of tail loss event ratios (the top 1% of historical loss amount-to-asset size ratios across covered firms).
3. Convert the drawn ratios to dollar values by multiplying the ratios by the total assets of firm *j* as of the quarter prior to the first quarter of the projection horizon of the stress test exercise.
4. Sum the converted draws. The summation represents one plausible realization of operational losses from 9-quarter tail loss events for firm *j* in event type *e*.

The simulation is performed 250,000 times per firm *j* and event type *e* to create a distribution of tail loss events for each firm-event combination.

b. Body Loss Event Modeling

The Board uses a simpler approach to model the body of the loss event distribution. The body of the loss event distribution constitutes all those loss events outside the top one percent of the distribution of industry loss-to-assets ratios. For these loss events, the Board's loss projections under supervisory scenarios reflect the expected body loss, defined as the average number of historical loss events multiplied by the average historical loss event amount for each firm and event type. Relative to a simulation, this expected loss approach is simpler and does not require as many assumptions. The approach also produces loss projections similar to that of a simulation.

For these loss events, the Board calculates the frequency ($\lambda_{j,e}^{body}$) as the historical average of the number of quarterly body loss events, multiplied by nine, for each firm *j* and event type *e*:

Equation A4 – Average Body Loss Event Frequency

$$\lambda_{j,e}^{body} = \frac{\#Body\ Events_{j,e}}{\#Quarters_{j,e}} \times 9$$

where $\#Body\ Events_{j,e}$ is the number of historical body loss events for firm *j* within event type *e*, and $\#Quarters_{j,e}$ is the number of quarters of historical operational loss data available for firm *j* within event type *e*.

The nine-quarter average body loss event frequency is multiplied by the average inflation-adjusted loss amount for a given firm *j* and event type *e*; the product represents expected operational losses from body loss events for that firm and event type ($BodyLoss_{j,e}$):

Equation A5 – Expected Operational Losses from Body Loss Events

$$BodyLoss_{j,e} = \lambda_{j,e}^{body}\ x\ \frac{\sum_{1}^{\#Body\ Events_{j,e}} Loss_{j,e}}{\#Body\ Events_{j,e}}$$

where $Loss_{j,e}$ is the loss amount from an event in the body of the loss event distribution for firm j in event type e.

Expected body losses are added to modeled tail losses for each of the 250,000 simulations to produce an aggregate loss distribution for each firm j and event type e.

c. Data and Ad-Hoc Adjustments for the Distributional Loss Model

The following adjustments are made to the data prior to estimation:

- As discussed in Section A.ii, loss events with a gross loss amount below $20,000 on an inflation-adjusted basis are removed from the estimation sample for the distributional model.
- As firms report the historical operational losses of acquired entities, asset size is constructed to include the assets of acquired entities.
- For the body and tail frequency models, the estimation dataset excludes loss events from the two most recent reporting quarters. As the frequency parameters are calibrated based on the average number of events over the reporting period, the two most recent quarters are omitted to prevent underestimation that might occur from a reporting lag. The data sample, however, is not truncated for purposes of constructing the severity distribution; the Board seeks to capture as many tail loss events as possible for this model component, and there would be no benefit from excluding the severity of loss events from the last two quarters.

d. Percentile Selection

The distributional model produces distributions of potential aggregate nine-quarter tail event losses for each firm j and event type e where a tail event is defined as a loss event in the top 1 percent of the industry loss-to-assets distribution. The Board uses the 93rd percentile from the simulated distributions to represent the magnitude of tail losses that might occur under stressed conditions, and this percentile is used to determine the distributional model's operational loss projections under the severely adverse scenario. This decision is discussed further in Section A.v.a.(3) below.

e. Treatment for firms with insufficient historical data

The distributional model requires that firms have collected historical operational loss data to calculate the individual firm tail loss frequency as shown in equation A1. However, in certain instances, firms may have a short time series of operational loss data, making it difficult to draw inferences from the frequency of historical tail loss events.[18] For a firm j under such circumstances, the Board does not use the distributional model but instead projects losses under the severely adverse scenario using the distributional model output based on the firm's asset size. In particular, nine-quarter operational loss projections for a new firm j, NF_j, are calculated as:

Equation A6 – Operational Loss Projections for a New Firm

$$NF_j = \frac{\sum_i \left(\frac{Loss_i^D}{TotalAssets_{i,t=0}}\right)}{N} \times TotalAssets_{j,t=0}$$

where $TotalAssets_{j,t=0}$ is the total assets as of the quarter prior to the first quarter of the projection horizon of the exercise for firm *j*; $TotalAssets_{i,t=0}$ are the total assets as of the quarter prior to the first quarter of the projection horizon of the exercise for a firm *i* that is modeled by the distributional model; $Loss_i^D$ is the nine-quarter operational loss projection under the severely adverse scenario for firm *i* produced by the distributional model, and *N* is the number of firms for which projections are produced by the distributional model.

[18] The Board typically follows the requirement that firms recently subject to the supervisory stress test have five years of data by event type to be included in the distributional model. This requirement is consistent with the Bank for International Settlements requirement for firms using the standardized approach for capital modeling. *See* BCBS (2023). *OPE Calculation of RWA for Operational Risk: Standardised Approach*. https://www.bis.org/basel_framework/chapter/OPE/25.htm#fn_OPE_25_10_3.

f. Adjusting for Loss Events Below the Modeling Threshold

As discussed above, the distributional model only projects operational loss events above the $20,000 modeling threshold. As loss data collection and reporting thresholds vary, this modeling threshold is necessary to ensure consistency in data inputs across firms. The Board chose the $20,000 threshold because it exceeds the vast majority of reporting thresholds across firms and business lines.

To account for losses that are not included in the input data for the distributional model, an additional model—the small-loss component model—estimates losses below the $20,000 threshold. Several firms report operational loss data without any threshold or one that is lower than this threshold. The Board utilizes these data to estimate loss events below $20,000. The small-loss component model is based on the observation that the share of smaller loss events does not vary much between firms, but that firms' total losses below this threshold are proportional to firm size, as measured by total assets. The small-loss component model averages asset-scaled aggregate losses from below-threshold events over time and across firms to project associated loss events based on asset size.

The small-loss component model consists of three steps. The first step is the calculation of the average quarterly ratio of below-threshold loss events scaled by total assets for each firm *j* and event type *e* reporting losses below the threshold:

Equation A7 – Firm-Level Average Quarterly Ratio of Below-Threshold Loss Events

$$BT_{j,e} = \frac{\sum_t \left(\frac{Loss_{j,e,t}}{TotalAssets_{j,t}} \right)}{\#Quarters_{j,e}} \times 9$$

where $Loss_{j,e,t}$ is the aggregated amount of loss dollars from loss events below $20,000 for firm j in quarter t and event type *e*; $TotalAssets_{j,t}$ are the total assets of firm j in quarter *t*; and $\#Quarters_{j,e}$ is the number of quarters where firm j reported below-threshold loss events.

The next step is to average firm-specific below-threshold ratios across firms within each event type:

Equation A8 – Average Below-Threshold Ratio

$$BT_e = \frac{\sum_j BT_{j,e}}{N_e}$$

where N_e is the number of firms that report below-threshold loss events for event type *e*.

Finally, projected loss events below the modeling threshold for each firm and within each event type under the severely adverse scenario are calculated as the average below-threshold ratio multiplied by the total assets of firm j as of the quarter prior to the first quarter of the projection horizon of the stress testing exercise, $TotalAssets_{j,t=0}$:

Equation A9 – Below-Threshold Adjustment

$$BTAdjustment_{j,e} = TotalAssets_{j,t=0} \times BT_e$$

In general, the $BTAdjustment_{j,e}$ is relatively small. In the 2024 stress test, the small-loss component accounted for about 2 percent of total projected losses across covered firms.

v. <u>Model Rationale</u>

A key feature of operational risk is the presence of large financial losses that stem from systemic events as well as idiosyncratic loss events that are specific to a single firm. The objective of the distributional model is to produce stressed operational loss projections that could be either systemic, correlated across several firms, or specific to individual firms. Examples of systemic loss events are those associated with the 2008 financial crisis. Examples of correlated events are litigation losses related to the London Interbank Offered Rate (LIBOR) manipulation and imposed on several firms at the same time. Finally, examples of loss events that are specific to individual firms include cybersecurity attacks that impact only a single firm. As the distributional model relies on the unconditional distribution of operational losses, it is sensitive to loss events that arise under a variety of circumstances. Loss projections are informed by idiosyncratic, correlated, and systemic loss events, all of which may coincide with severe macroeconomic deterioration.[19]

The distributional model is derived from a class of models known as the LDA. Unlike the methodologies that many covered companies use to project their own operational losses, the distributional model is not meant to capture exposures to specific operational loss events of individual firms. Covered companies are encouraged to engage in risk identification and produce loss projections that reflect the types of operational risks specific to their business models.[20] The distributional model, by contrast, is informed by industry experience across firms; consistent with the stress testing principles of simplicity, consistency and comparability, a standard set of assumptions apply to all firms and differences in outcomes are explained by differences in input data. By taking a tail percentile of the unconditional aggregate loss distribution, the model produces a conservative loss estimate that accounts for a range of different risks that firms may face.

Some of the key decisions related to the operational loss distributional model are explained below.

[19] The Board has explored alternative models that explicitly incorporate macroeconomic factors. One such alternative is described below in Section A.vi.a.

[20] The Board provides guidance to firms for capital planning purposes. *See* Board of Governors of the Federal Reserve System (Dec. 18, 2015, rev. Jan. 15, 2021), *SR 15-18*. https://www.federalreserve.gov/supervisionreg/srletters/sr1518_pw.pdf

a. Modeling the Body and Tail of the Severity Distribution Separately

As discussed above, the Board models the body and tail of the loss event severity distribution separately and differently. This separation is appropriate for two reasons. First, frequency is significantly different for body losses and tail losses. Body losses occur frequently, which enables the use of individual firm data to model severity reliably. In contrast, tail losses are infrequent and severe. Thus, modeling tail severity using each individual firm's own loss data is highly sensitive to the addition of a few tail losses. As such, tail severity is modeled using loss data from all firms, which enables a more stable model output. Second, the correlation between firm size and operational loss magnitude is different for body losses and tail losses. The literature shows that tail losses correlate with firm size (Cope and Labbi, 2008; Abdymomunov and Curti, 2020).[21] As such, the model uses tail losses scaled by firm size to obtain a severity ratio, which enables comparison of tail loss severity across firms of different sizes. On the other hand, the literature also shows that body losses do not directly relate to firm size (Abdymomunov and Curti, 2020). Thus, body losses are not scaled by asset size and are instead projected based on average historical body loss severity.

The body-tail cutoff point is based on the findings of Abdymomunov and Curti (2020), who show that, starting from the 99th percentile of the pooled industry loss distribution, total assets correlate significantly with the size of operational losses.

[21] *See* Cope, E., and Labbi, A., 2008. Operational loss scaling by exposure indicators: Evidence from the ORX database. *Journal of Operational Risk*, 3(4), 25–46; Abdymomunov, A., and Curti, F., 2020. Quantifying and Stress Testing Operational Risk with Peer Banks' Data. *Journal of Financial Services Research*, 57(3), 287–313.

(1) Rationale for Using a Poisson Distribution for Frequency Modeling

As discussed above, the Board uses a Poisson distribution to model tail loss event frequency. The Poisson distribution is a standard distribution used to model count processes[22] and is suitable in this context as the historical data fit the distributional properties well. Alternative distributions that are commonly used to model count processes, such as the negative binomial distribution, would increase the complexity of the model without significantly improving model outcomes. In particular, the Poisson distribution involves fitting a single parameter, while alternatives often involve fitting several parameters. The Board tested more complex alternatives and found that they did not fit the historical data better across the range of covered firms. Consistent with the principle of simplicity as stated in the Stress Testing Policy Statement, the Board determined that the potential benefits of using an alternative frequency distribution were not sufficient to justify the added complexity.

(2) Using Historical Loss Events for the Severity Distribution

The Board also explored alternative distributional models in which loss severity is assumed to follow a known parametric probability distribution. In these models, a heavy-tailed probability distribution—such as the log-normal or Pareto distribution—are parameterized based on historical data. During the Monte Carlo simulation, draws are made from the parameterized distribution rather than from the pool of realized historical tail events, as is done with the chosen model.

A limitation of the chosen distributional model is that severity draws are made from a fixed pool of realized loss events, which can limit the range of possible outcomes. Making a distributional assumption about loss event severity could help overcome this limitation, as there

[22] A count process refers to a data-generating process that produces non-negative, integer outcomes. The frequency of operational loss events in a given time span is an example of a count process.

would be no upper limit on the size of drawn loss events. In practice, however, parameterized severity distributions are unstable over time; when distributions are fit to heavy-tailed data, the parameterization is very sensitive to the introduction of new data, particularly new tail loss events. The sensitivity to new data translates to model loss projections that can change substantially from stress testing cycle to cycle. Stress test modeling principles emphasize the importance of stability in loss projections over time; stability is important for ensuring that changes in stress loss estimates reflect underlying risk factors rather than sudden changes in data inputs. As the parameterized severity distributions tended to produce excessive year-over-year variation in stress loss projections, the Board determined it was appropriate to use the more stable distributional model.

(3) Using the 93rd Percentile of the Aggregate Loss Distribution for the Severely Adverse Scenario

The Board uses the 93rd percentile of the distributional model's aggregate loss distribution to represent projected operational losses under the Severely Adverse Scenario. The 93rd percentile is chosen based on the frequency of severe recessions. More specifically, in the 60 years from 1956 to 2015, when this practice was first adopted, nine recessions occurred, four of which were severe.[23] Thus, the calculated frequency of severe recessions is 4 in 60 years or roughly an event that happens once every 15 years. This frequency suggests a draw from the 93rd percentile of the aggregate loss distribution.[24]

b. Questions

Question A1: What are the advantages and disadvantages of using a distributional model to estimate operational risk losses? What is the appropriate percentile for the model?

[23] The timeframe and recession classification are consistent with those used to formulate scenario design policy. *See* 12 CFR 252, Appendix A.

[24] The 93rd percentile is derived as follows: $1 - \frac{4}{60} \approx 0.93$.

Question A2: As discussed above, the Operational Risk Model uses a Poisson distribution for loss frequency modeling. What are the advantages and disadvantages of using this distribution? Are there alternative distributions or modeling approaches the Board should consider?

Question A3: As mentioned above, the Board models the body and tail of the operational loss severity distribution separately. What are the advantages and disadvantages of modeling sections of the overall distribution separately?

vi. Alternatives to the Distributional Model

The Board has explored many alternatives to the distributional model for the purpose of projecting operational losses. Two notable challenger models that the Board uses to benchmark loss projections are discussed below.

a. Macroeconomic Regression Model

The Board used an operational loss regression model for several stress testing cycles alongside the distributional model. However, the Board is proposing to discontinue using the macroeconomic regression beginning with the 2026 stress test. The regression model forecasts operational losses as a function of macroeconomic variables. Academic literature has established a broad link between operational risk and the macroeconomy or macroenvironment (e.g., Hess, 2011 and Abdymomunov, et al., 2020).[25] Relative to the distributional model, which produces an unconditional loss projection, the regression model produces forecasts that are conditional on the macroeconomic environment. Relative to the distributional model, however, the regression model has several shortcomings. As discussed below, the regression model lacks robustness and is

[25] *See* Hess, C. The impact of the financial crisis on operational risk in the financial services industry: empirical evidence. *The Journal of Operational Risk* 6.1 (2011): 23; Abdymomunov, A., et al., 2020. U.S. banking sector operational losses and the macroeconomic environment. *Journal of Money, Credit, and Banking*, 52(1), pp. 115–144.

sensitive to data inputs. Further, some operational losses, particularly large legal losses, take several years to unfold; the lag between the start and end date of some operational loss events can make it difficult to confidently capture the relationship between operational risk and the state of the macroeconomy.

In the first step, it projects industry-aggregated losses for the covered firms over the projection horizon. In the second step, it allocates the aggregate loss projection to individual firms based on the estimated relationship between firm size and the realization of operational losses.

(1) Industry Loss Model (Step One)

First, a linear regression model is used to model and forecast industry-aggregate quarterly operational losses scaled by industry assets as a function of macroeconomic variables. The variables are the level and the four-quarter difference in the unemployment rate; the level and the four-quarter difference in the spread between the 10-year U.S. Treasury and BBB index; the U.S. Volatility Index (VIX); and the four-quarter growth in the Housing Price Index (HPI). Industry-aggregated operational losses, scaled by industry-aggregated assets, are estimated according to equation A10 below:

Equation A10 – Linear Regression Model for Industry Operational Losses

$$\frac{Loss_t}{Assets_t} = \alpha + \beta \times (PC1_t) + \varepsilon_t$$

In equation A10, $Loss_t$ is the total gross operational loss amount aggregated across covered firms and event types in quarter t;[26] $Assets_t$ are the Total Assets aggregated across covered firms

[26] Except for losses due to the damage to physical assets.

in quarter *t*; and $PC1_t$ is the first principal component[27] from the six macroeconomic variables described above and estimated at quarter *t*.

Using this specification, the model projects loss-to-asset ratios over each quarter in the projection horizon and converts them to dollar losses by multiplying them by bank industry assets as of the quarter immediately preceding the first quarter of the projection horizon. Firm asset size is assumed to stay constant over the projection horizon.

(2) Loss Allocation Model (Step Two)

Second, a linear regression is used to estimate weights to distribute estimated industry losses to individual firms. The generated weights are based on the following linear regression model:

Equation A11 – Linear Regression Model to Estimate Firm Weights

$$ln(Loss_{j,t}) = \alpha + \gamma \times ln(Assets_{j,t}) + \varepsilon_{j,t}$$

In equation A11, $Loss_{j,t}$ is the total gross operational loss amount in quarter *t* for firm j, and $Assets_{j,t}$ are the total assets in quarter *t* for firm j.

Allocating losses based on a risk indicator, in this case asset size, is consistent with stress testing model principles, which de-emphasize firm-specific estimation and the assumption that past performance will persist in the future. The allocation method is a simple way to arrive at firm-level projections without relying on the loss history of any firm. Further, there is a strong cross-sectional correlation between the size of firms and the size of their operational losses; the

[27] To measure and represent the macroeconomic environment, the Board constructs a broad measure of macroeconomic activity. A natural approach for condensing information into a single measure is the statistical dimension-reduction method known as principal component analysis (PCA). The principal component captures common variation amongst the chosen macroeconomic variables in a single variable. Using PCA is desirable for its simplicity. It also helps avoid econometric issues with multi-collinearity—or the tendency of dependent variables to be highly correlated—which is a common feature amongst macro-economic variables.

coefficient (γ) produced by equation A11 exhibits strong statistical significance. The logarithmic specification in equation A11 reflects a pattern in historical operational loss data: operational losses exhibit a non-linear relationship to asset size. That is, an increase in firm size yields higher increases in expected operational losses. As such, forecasted operational losses tend to be distributed non-linearly in relation to asset size.

(3) Projected Losses of the Operational-Risk Loss Regression Model

Finally, total industry projected losses for each quarter of the projection horizon calculated in step one are calculated for each individual firm using the distributive weights calculated in step two. More specifically, the coefficient estimates from equation A11 are used to estimate the expected operational losses for each covered company:

Equation A12 – Expected Operational Losses

$$\widehat{Loss_{j,t=0}} = \exp\left(\hat{\alpha} + \hat{\gamma} \times \log\left(Assets_{j,t=0}\right)\right)$$

where $\hat{\alpha}$ and $\hat{\gamma}$ are parameter estimates from the regression model shown in equation A11. For firm *j*, the share of losses from the industry-aggregate loss projection is calculated as:

Equation A13 – Firm Share of Losses

$$s_j = \frac{\widehat{Loss_{j,t=0}}}{\sum_j \widehat{Loss_{j,t=0}}}$$

The operational-risk loss projection for firm *j* in projection quarter *t* is calculated as the product of the firm's share of losses and the industry-aggregate loss projection for that quarter:

Equation A14 – Firm Loss Projection

$$Loss_{j,t} = s_j \times Loss_t^{Industry}$$

where $Loss_t^{Industry}$ denotes the industry-aggregate loss projection for projection quarter t produced by the industry regression (equation A10).

The operational loss regression model has several limitations that render it less appropriate than the distributional model for projecting operational-risk losses. First, the regression model lacks robustness and performs inconsistently across different types of economic crises. Many firms experienced large operational losses stemming from the 2008 financial crisis, which, among other things, revealed deficiencies in underwriting practices. However, the relationship between the macroeconomy and operational losses is less pronounced during other stressed periods included in the estimation sample. Second, the regression model is highly sensitive to the timing of operational loss events. Many large legal loss events started unfolding during the 2008 financial crisis, but it took several years for their financial impact to be fully realized. Unless it is assumed that the financial impact of an operational loss event is realized immediately, the regression model's estimated sensitivity of operational losses to macroeconomic variables is diminished when accounting for the lag between when an event begins and when the financial impact is realized. Finally, the regression model is, in general, very sensitive to a relatively small number of large loss events. When using alternative regression frameworks that account for statistical outliers, the model's sensitivity diminishes considerably. Given the shortcomings noted above, and the distributional model's relative robustness to issues around data outliers and loss timing, the Board prefers the distributional model for purposes of projecting operational losses.

(4) Questions

Question A4: Should the Board consider using the macroeconomic regression model instead of the distributional model? What would be the advantages and disadvantages of using *the regression model to estimate operational-risk losses? Are there other regression model specifications that the Board should consider?*

b. Business Line-Based Model

A key feature of the operational loss model is the use of firm asset size as an indicator of exposure to operational risk. The Board explored a challenger approach that uses a range of alternatives to total assets as risk indicators. The intent of the challenger model is to project operational losses based on the amount and type of business activities occurring at the firms, rather than on their asset sizes. In contrast to the chosen approach, in which operational losses are segmented by the reported Basel event type, the challenger model ties different indicators of operational risk to different operational losses categorized by the Basel business line as reported on the FR Y-14Q. As shown in **Table** A2 below, many of these alternative indicators are proxied by different sources of revenue, which were chosen to serve as alternatives to total assets. As discussed below, the challenger model exhibits some desirable properties; however, using revenue-based scaling variables has some disadvantages relative to the distributional model. In particular, revenue is generally more volatile than asset size, and this volatility can be driven by factors with little association with operational risk, such as monetary policy. As such, the challenger model is often more unstable than the distributional model, and stress loss projections can change for unintuitive reasons.

Business activities are proxied by different indicators of exposure to operational risk for different business lines. These indicators were selected based on model fit criteria and are shown in **Table** A2 below.

Table A2 – Challenger Model Proxies for Business Activity

Model Business Lines	Activity Proxy	Source
Retail & Commercial Banking	Interest Income - Interest Income from Trading Assets + Bank and Credit Card Fees	FR Y-9C
Corporate Finance	Value (USD) of Equity Offerings and M&A Deals Advised	Third-party Vendor
Sales & Trading	Interest Income from Trading Assets	FR-Y9C
Other	Payment & Noninterest Income - Bank and Credit Card Fees	FR Y-9C

Note: The FR Y-14Q reporting form includes nine different categories for the Basel Business Line variable. For purposes of modeling, these are condensed to four categories.

The challenger model produces industry loss projections for the severely adverse scenario over the nine-quarter projection horizon by first normalizing historical nine-quarter loss amounts by their respective proxies for business activity. Losses are matched to activity levels lagged four quarters to account for the differences in timing between the discovery dates and accounting dates noted in the estimation data. Industry loss projections are then generated by taking the product of a selected percentile of the normalized loss amounts and the nine-quarter sum of the activity proxy prior to the beginning of the projection horizon:

Equation A15 – Industry Operational Loss Projections

$$IndustryLossForecast_{[t,t+9Q]} = 9QnormalizedLosses \quad \times 9Qactivity_{t-4Q}$$

In equation A15, $IndustryLossForecast_{[t,t+9Q]}$ is the industry loss projection over the projection horizon, $9Qactivity_{t-4Q}$ is the sum of the business activity proxy over the nine-quarter period that ends four quarters prior to the beginning of the projection horizon, and $9QnormalizedLosses$ is the 93rd percentile of the distribution of historical nine-quarter loss amounts scaled by historical business activity proxies.

Industry loss projections are allocated to firms based on a measure of exposure to operational losses within each of the modeled business lines:

Equation A16 – Firm Operational Loss Projection

$$OpLossForecast^{j}_{[t,t+9Q]} = Exposure^{j}_{t} \times IndustryLossForecast_{[t,t+9Q]}$$

In equation A16, $OpLossForecast^{j}_{[t,t+9Q]}$ is the projection for firm j over the projection horizon, $IndustryLossForecast_{[t,t+9Q]}$ is the industry loss projection over the projection horizon, and $Exposure^{j}_{t}$ is a measure of exposure to operational risks within the respective modeled business line for firm j that is calculated as:

Equation A17 – Exposure to Operational Risk by Business Line

$$Exposure^{j}_{t} = \frac{f\left(ActivityShare^{j}_{[t-4Q,t-1Q]}\right)}{\sum_{j} f\left(ActivityShare^{j}_{[t-4Q,t-1Q]}\right)}$$

where $ActivityShare^{j}_{[t-4Q,t-1Q]}$ is the share of business activity of bank j in a business line over the four quarters before the start of the projection horizon, measured by the activity proxy presented in **Table** A2. The function f represents a relationship between the share of losses and the share of one-year lagged activity.

The challenger model has some desirable properties relative to the distributional model. By segmenting historical losses by business line, the model produces loss projections that are intuitive, as they are informed by firms' business models. For instance, firms that have large investment banking businesses are particularly sensitive to the proxy used to capture activity in the Sales & Trading business line; for credit card companies, however, Sales & Trading has little impact. The distributional model lacks this level of granularity because it uses total assets as the sole measure of exposure.

However, the challenger model also has limitations that render it less appropriate than the distributional model for projecting operational-risk losses. First, the Board has found that it can be difficult to select appropriate risk indicators for specific business lines due to the idiosyncratic nature of many operational loss events; many losses, including in the tail of the distribution, arise for reasons that have little to do with the amount of business activity within a certain area.[28] Second, the model is driven heavily by different revenue components, as seen in **Table** A2. These were chosen to provide a benchmark to the distributional model, which is driven by asset size, but these revenue components can be unstable over time, even when taking four- or eight-quarter averages. The volatility in revenue components, further, can stem from economic factors that do not have an intuitive association with operational risk, such as monetary policy and the interest rate environment. The lack of stability from these risk indicators translates to more volatile loss projections, which is an undesirable feature for stress testing models, particularly when the volatility may be driven by unintuitive reasons.

c. Questions

Question A5: Is there any other alternative model that the Board should consider to estimate operational-risk losses? What would be the advantages and disadvantages of using that alternative to estimate operational-risk losses?

Question A6: As noted, the distributional model produces an unconditional distribution. Are there macroeconomic, financial, or firm-specific variables that the Board should consider in modeling operational-risk losses? If so, what are they? What data source could the Board use to incorporate those additional variables, and how could they be incorporated into the model? What would be the advantages and disadvantages of incorporating those additional variables?

[28] For instance, operational losses from a rogue trading event may be idiosyncratic and disconnected from the overall amount of trading happening at a firm.

vii. Assumptions and Limitations

For the reasons set forth in Section v, the Board believes that the Operational Risk Model is a reasonable method for projecting operational-risk losses for the firms subject to the supervisory stress test. Nevertheless, the Operational Risk Model relies on certain key assumptions, which are discussed below.

a. Loss Timing and Recognition

The Board makes certain assumptions about the timing of each loss event. In particular, the Board uses the reported accounting date for purposes of timing loss events and assumes, for a loss event with several reported accounting dates, that the full financial impact occurs within a single quarter.[29] As discussed below, the Board found this assumption reasonable, as the model is generally robust to alternative assumptions, and conservative, as it assumes firms may need to incur the full financial cost of an operational event within a single quarter. The assumption is also practical, as it yields consistent data across firms that report their loss events differently.

The Board uses the reported accounting date on the FR Y-14Q to timestamp loss events because it is more reflective of the financial impact of operational loss events than other reported dates. According to the FR Y-14Q reporting instructions, covered firms are required to report an occurrence date as well as an accounting date for each loss event. The occurrence date is meant to capture when the event that resulted in a financial loss began, and the accounting date reflects when the financial impact was reflected on the firm's financial statements. While for most loss events the occurrence and accounting dates are close in time to each other, some types of losses can have long time lags between the two dates. The Board believes that using the accounting date

[29] Specifically, for instances where firms report several accounting dates for a loss event, the financial impacts from the loss event are assumed to be experienced as of the first reported accounting date. For the distributional model, the decision on where to timestamp an aggregated loss event determines which value of total assets is used to scale the aggregated loss amount. Outside of this, the timestamping has no other impact on model outputs.

is more consistent with the primary goal of the stress test, which is to, "evaluate the financial resilience of banks by estimating losses, revenues, expenses, and resulting capital levels under hypothetical economic conditions" (Board of Governors, 2024).[30] Unlike the occurrence date, the accounting date captures when the loss event was recorded on firms' financial statements and thus is the better date from which to assess the financial impact of operational loss events.

Some firms report more than one accounting date for loss events that unfold over time. For these loss events, the Board assumes that the full financial impact occurred within a single quarter. The Board makes this assumption for practical reasons and for conservativeness.

From a practical standpoint, firms have different standards for establishing legal reserves and different loss reporting practices; rather than reflecting the dates that legal reserves were established or increased, the accounting date might reflect the settlement or payment date for some firms. In such instances, the reported accounting date may not represent the dates the firm was impacted financially. As such, aggregating the full impact of a loss event to a single quarter standardizes data across firms, improves interpretability, and mitigates issues with heterogenous reporting practices.

Finally, the practice of aggregating loss events to a single quarter is conservative, as it assumes the financial burden of an event may be experienced all at once, rather than smoothed over time. While operational loss events can, in the extreme, take several years to be fully realized, most of the financial impact from most loss events occurs within a relatively short period of time. Specifically, on a loss-weighted average, most of the financial impact of a loss event occurs within a nine-quarter window. This average is skewed downward by large legal events; for the vast

[30] *See* Board of Governors of the Federal Reserve System, *2024 Supervisory Stress Test Methodology* (March 2024), https://www.federalreserve.gov/publications/files/2024-march-supervisory-stress-test-methodology.pdf.

majority of loss events, the full financial impact is realized within a nine-quarter period. Further, the distributional model is generally robust, and loss projections change only modestly when using data as it is reported rather than aggregating to a single quarter.

(5) Questions

Question A7: What are the advantages and disadvantages in assuming that the full financial impact occurs within a single quarter when it is first reported for modeling operational-risk losses in the supervisory stress test?

Question A8: Should the Board consider modifying or eliminating the assumption around loss timing? If the Board were to eliminate the assumption, how should the Board address concerns around the heterogeneity of firms' data collection and accounting practices? What would be the advantages and disadvantages of that change?

b. Total Assets as a Scaling Variable

Total assets is used throughout the Operational Risk Model as a proxy measure for firms' exposure to operational risks. For each modeling component, total assets is used as a scaling variable to normalize historical operational losses across firms and over time.

The Board found total assets a suitable scaling variable for several reasons. First, total assets is a broad measure of the size and extent of business activities, which is desirable given that operational risk is prevalent throughout nearly every business line of a banking organization. Additionally, asset size is a proxy measure for firm complexity; larger banking firms tend to engage not only in a broader volume of business activities but also in a broader range of more sophisticated types of business activities, making them more prone to operational risk. Thus, total assets serves as an indicator not only of business volume but also of the risk that arises with increasing business complexity.

Academic research supports the use of total assets in the Operational Risk Model. Curti et al. (2022)[31] show that the relative size of a banking organization is related to operational risk exposure and that the largest firms have higher operational losses per dollar of assets. Abdymomunov and Curti (2020) show that asset size is significant in explaining large operational loss realizations, and scaling by asset size across firms with different characteristics can increase the stability of loss estimates relative to estimates produced for a firm using only its own data. This finding motivates the scaling of loss events in the distributional model and the production of a simulated aggregate loss distribution for each firm based on an industry pool of tail loss events.

The Board explored alternative operational risk indicators. In particular, the merits of using total income, total assets without cash equivalents and other liquid assets, and risk-weighted assets are discussed below. The Board is proposing to start using total assets without cash equivalents and other liquid assets (option 3 below) beginning in the 2026 stress test.

1. **Total Income:** The Board considered using total income rather than total assets, as it reflects the revenue earned within firms, including from business lines that may contribute little to firms' asset sizes. For instance, transaction processing involves a great deal of back-office activity that does not appear on the balance sheet. As such, revenue-based measures may better capture the overall level of business activity than asset-based measures. Revenue measures, however, have some undesirable properties as a measure of operational risk exposure. First, firm revenue tends to decrease dramatically during recessions. This could lead to circumstances where operational loss projections decrease suddenly during periods of economic stress, which is not aligned with historical data and the 2008 financial crisis experience. Further, and as noted earlier, total income exhibits much higher volatility over time than do asset-based measures and would introduce greater volatility to operational loss projections. As a result, the Board determined that total assets was preferable to total income for scaling historical operational losses.
2. **Total Assets without Cash and Cash Equivalents:** The Board also considered total assets less cash and cash equivalents**.** Cash equivalents, such as reserves held with central banks, can fluctuate depending on factors without much relevance to operational risk, such as monetary policy, and can introduce additional volatility into loss projections. Total assets increased substantially for covered firms during the COVID-19 pandemic, an

[31] *See* Curti, F., et al., 2022. Are the largest banking organizations operationally more risky? *Journal of Money, Credit and Banking*, 54(5), pp. 1223–1259.

outcome driven largely by increased cash holdings rather than factors with an intuitive association with operational risk. While intuitive, there is little quantitative support for removing cash equivalents from total assets. Specifically, panel regression results show that total assets have similar sample fit properties than do total assets without cash equivalents for purposes of explaining operational losses. As stress testing focuses on economic recessions, the Board also analyzed recessions and non-recession periods separately. Whether during an economic recession (2008 financial crisis or the COVID-19 pandemic) or otherwise, total assets exhibited similar goodness-of-fit compared to total assets without cash equivalents.

3. **Total Assets without Significant High-Quality Liquid Assets:** The Board also considered total assets less major components of assets defined as Level 1 high-quality liquid assets (HQLA) for purposes of calculating the Liquidity Coverage Ratio (LCR).[32] Level 1 HQLA includes cash and those assets that are generally most easily converted into cash. For purposes of subtracting Level 1 HQLA from total assets, the Board has generally used a proxy measure for ease of implementation; the proxy includes cash and cash equivalents, U.S. Treasury securities, and U.S. government agency obligations, which collectively comprise most of Level 1 HQLA. As described above, cash and cash equivalents can be volatile and may fluctuate based on policy circumstances without much relevance to operational risk. One may further argue that cash and U.S. government securities are not complex assets and may not confer much operational risk to covered companies. For instance, it could be argued that there is little legal risk or potential for fraud when transacting in U.S. Treasury securities. Further, hypothetical analyses do show greater stability of operational loss projections when subtracting out the proxy for Level 1 HQLA currently in use. As loss projections tend to move proportionately with the chosen scaling variable, using a more stable scaling variable tends to result in more stable loss projections. In this instance, subtracting the proxy for Level 1 HQLA would have yielded more stable loss projections in recent stress testing cycles, particularly through the COVID-19 pandemic period. However, similar to the outcomes when subtracting only cash and cash equivalents, this measure tends to exhibit similar goodness-of-fit performance compared to total assets for predicting future operational losses. However, given the enhanced stability for predicting future operational losses using this approach, the Board is proposing to exclude the aforementioned proxy of Level 1 HQLA from total assets beginning with the 2026 stress test.
4. **Risk-weighted Assets:** The Board also considered using risk-weighted assets (RWA) calculated under the standardized approach. RWA is appealing because it is intended as a measure of the level of firm-specific risk over time. Using RWA, however, has practical and conceptual disadvantages. First, RWA is a regulatory calculation that has changed over time. Therefore, it may introduce time variation unrelated to changes in operational risk. Further, RWA is weighted heavily by measures of credit and market risk. By using RWA, the model would imply an association between operational risk and these other types of risk. For instance, if a firm increases its exposure to credit risk, the use of RWA

[32] The Liquidity Coverage Ratio is a measure of the liquidity of a firm's holdings, or the ability of a firm to quickly convert its holdings to cash. For more information on the LCR and HQLA, *see* Bank for International Settlements, 2013. *Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools*. https://www.bis.org/publ/bcbs238.pdf.

in the Operational Risk Model would imply an equivalent increase in exposure to fraud, systems issues, and other operational risks.

(1) Questions

Question A9: What are the advantages and disadvantages in using total assets to scale historical operational losses in the supervisory stress test?

Question A10: What are the advantages and disadvantages in adjusting total assets by removing cash and cash equivalents or other liquid assets for purposes of estimating and projecting operational losses? Are there certain asset classes that should be removed from the scaling measure? If so, what are these asset classes? What are the advantages and disadvantages of using these other asset classes?

Question A11: Are there additional data items reported on the FR Y-9C, FR Y-14, or other relevant regulatory forms, or available elsewhere, that the Board should consider incorporating in its modeling of operational-risk losses instead of total assets? If so, which ones? What would be the advantages and disadvantages of such additional data items?