

Article

Stress-testing models: a strategic risk management tool

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Executive summary

Stress-testing models: a strategic risk management tool

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Stress-testing has become a critical component of risk management, but the information it produces is only as reliable as the underlying model used. As such, this paper highlights the importance of using a variety of models and methodologies to produce a diagnosis of a bank's health.

Stress-testing models: a strategic risk management tool

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Abstract

This paper discusses the role of models in conducting stress-tests for regulatory and risk management purposes, and presents some approaches that may enhance their ability to estimate outcomes in a stressful environment. Unlike a conventional model that is designed for a steady state environment, we argue that a stress-testing model needs to be developed with a different design to capture the implications of abnormal business and economic conditions. Developing such a model may require a combination of qualitative and quantitative adjustments to capture the stress or boundary conditions. Consequently, the governance needs of stress-testing models require more rigor than steady state models to effectively challenge the underlying construct and assumptions. It is critical that senior management appreciate these nuances before using the output of such models for key strategic decisions.

Risk management in the financial services industry has continued to evolve and adapt to new or unforeseen combination of risks. The recent financial crisis has highlighted the previously unrecognized high degree of correlation across and within asset classes, particularly when faced with a deteriorating economic environment. During this period, the common economic shocks (e.g., decline in house prices, rise in the unemployment rate, increased volatility in the stock market, etc.) affected multiple portfolios simultaneously, albeit with different lag times. During this turbulent time, the fundamental weaknesses in the market coupled with in some instances a lack of an ability to anticipate the degree of concentrated risks brought many institutions in the U.S. and elsewhere to the brink of insolvency. This resulted either in outright bankruptcy, an orderly acquisition engineered by the regulators, or recapitalization of the bank by regulators. The need for stress-testing in financial services was accentuated during this tumultuous period as this crisis unraveled and the ability to understand the implications of likely future projections became critical both for regulators and the industry. The concept of using a stress-testing framework gained immense strategic importance as bank senior management and the board of directors, as well as the regulators, tried to grapple with the outcome of the domino effects. Coming out of the crisis, stress-testing has emerged as one of the most critical regulatory tools in a post-crisis effort to avoid such outcomes in the future.

The term “stress-testing” is commonly applied in the medical profession, where cardiologists routinely stress-test the human cardiovascular system to evaluate adequate supply of blood to vital organs. The stress-testing of the banking system focuses on ensuring adequate capital, which is not too far from the analogy of the human body since capital serves as the life blood of a financial institution and an abrupt shortage of which could not only cause financial distress but also potential insolvency. However, the parallel between the banking and medical stress-tests breaks down in the implementation of this concept across the two fields. While the human body can be stressed in a limited manner under controlled conditions to evaluate the body's cardiovascular response to potentially stressful conditions requiring higher than normal levels of exertion, the same realistic experiment cannot be conducted on a bank to evaluate different stressful scenarios even on a limited basis without causing significant financial losses and business disruptions. The practical

approach, therefore, is to use a model¹ (or a set of models) that represents a bank's balance sheet and portfolio to simulate the stressful scenarios. The model proxies the bank's portfolio and provides an assessment of its financial condition under various circumstances, simulating alternative future outcomes.

Consequently, it is imperative that such models have the capability to simulate alternative macroeconomic or other scenarios as realistically as possible to assess the bank's solvency, as well as build in sufficient portfolio sensitivity to those scenarios. The models need to impose appropriate profit and loss implications to draw some realistic conclusions about the bank's financial condition under multiple stress conditions. Needless to say, the effectiveness of the underlying models used to conduct the stress-tests is critical in reaching a viable diagnosis of a bank's financial health, otherwise we may cause unnecessary alarm and panic or alternatively fail to identify a significant risk (also referred to in statistical terms as Type I or Type II error, otherwise known as false positives or false negatives). The effectiveness of the entire stress-testing exercise, therefore, relies heavily on the ability of the model(s) to adequately represent the bank's portfolio, and its ability to capture the impact on the portfolio of a stressful internal or external scenario.

The quality of information coming out of a stress-testing exercise is dependent on the thoroughness of the process and the effectiveness of the underlying models. The results of a robust stress-testing process can provide immense insight into the probable scenario-driven outcomes, and offer a valuable means of preparing for the potential challenges. Institutions with these capabilities are able to anticipate and prepare for the adverse conditions. Stress-testing is also an important element of the prudential supervision process that permits regulators to draw conclusions about the health of a bank and develop appropriate regulatory responses based on that outcome. Conversely, model risks and limitations associated with the stress-testing models, if not understood and mitigated where necessary, can lead to false conclusions about the bank's ability to sustain a stressful outcome. Hence, of all the different requirements that are necessary for conducting stress-testing, a well-functioning model(s) represents a crucial component of that process.

¹ The term model is used generically to describe a qualitative or quantitative approach that forms the basis of future projections.

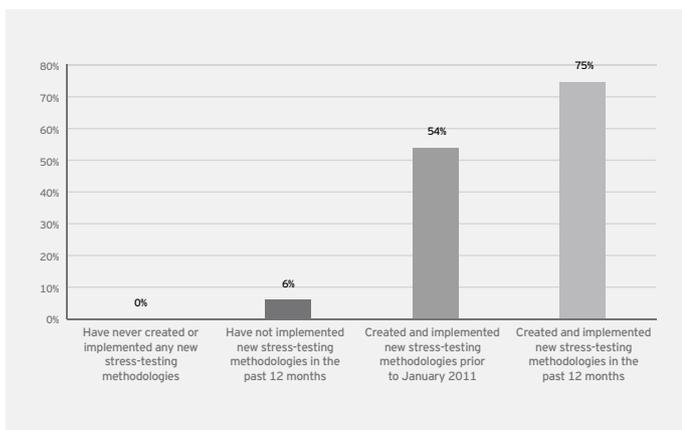


Table 1: Firms continue to implement new stress-tests²

Source: EY/IIF 3rd Annual Survey of Risk Governance (2012)

Greatest problem is speed – stress-tests take 3 months or more and are too cumbersome to use as a flexible management tool

As stress-testing is evolving in the banking industry, this paper describes some of the modeling challenges in stress-testing and offers insights into methodologies used in the industry, regulatory expectations, and the means to ascertain the effectiveness of such models. Furthermore, this paper offers critical insights to senior management as they utilize the stress-testing results for strategic needs, such as determining the risk appetite of the bank, and provides them with guidance on how to effectively challenge the underlying models before accepting their output.

Background

Even though the Basel II global capital accord formulated in the early 2000s specifically called out the need for conducting stress-testing, their criticality and the value did not become fully apparent as an important risk management tool until the 2007-2008 financial crisis in the U.S. As the crisis was unraveling, a number of financial institutions hurriedly undertook significant stress-testing exercises focused primarily on their mortgage exposures to fully comprehend the impact of changing housing market conditions. Some of the early adopters were able to plan ahead and partially mitigate the impact of the “housing bubble.” A number of post-crisis regulatory initiatives and subsequent

legislation emphasized stress-testing of bank portfolios as an important prudential supervisory tool. The Supervisory Capital Adequacy Program (SCAP) conducted by the Federal Reserve in early 2009 drew significant media and public attention as it was the first publicly disclosed effort to ascertain the health of the banking sector post-2008 financial meltdown. Since then, the stress-testing exercise has been codified in the U.S. via standard regulatory tools for ongoing prudential supervision, namely the Comprehensive Capital Analysis and Review (CCAR) and the Dodd-Frank Act Stress Tests (DFAST) requirements.³ CCAR is an annual exercise by the Federal Reserve to ensure that the largest bank holding companies have sufficient capital to continue operations throughout periods of economic and financial stress, as well as robust, forward-looking capital planning processes that account for their unique risks.⁴ Based on the outcome of the CCAR stress-tests and qualitative review, U.S. regulators may approve, curtail, or reject any proposed capital actions planned by the bank during the year. Furthermore, public disclosure of the stress-testing results puts added pressure on bank management to appropriately inform investors about their risks. The regulatory requirements specify the economic scenarios that banks have to utilize to project their stress-testing outcomes. These future scenarios include baseline or neutral and (severely) adverse scenarios. Over time, the number of economic variables provided by the regulators, against which the stress-testing outcomes have to be projected, have grown, recognizing both the increasing reliance by regulators on stress-testing for supervision purposes as well as the multi-faceted linkages to a bank’s portfolios. For example, some of the earlier stress-testing requirements immediately after the financial crisis were limited to scenarios defined by a handful of economic drivers such as GDP, home price, and unemployment. These have recently been expanded to also include macro-economic changes in the Eurozone that has implications for internationally-active banks. As part of the CCAR process, U.S. regulators have developed an independent set of stress-testing models designed to use bank data to analyze the impact of different economic conditions. The independent regulatory stress-testing models are a mechanism to guard

² Percentages in the figure across choices may sum up to more than 100%, as not all survey choices are mutually exclusive.

³ Similar to the Dodd-Frank Act in the U.S., other jurisdictions like the FSA in the U.K. have also enacted similar regulations that require banks to conduct periodic stress-testing of their portfolios.

⁴ Currently, there are 18 BHCs that are required to submit their capital plans to the Federal Reserve on an annual basis as part of the CCAR. In addition, there are an additional set of 11 BHCs that are also required to submit their capital plans as part of the Capital Review Process (CapPr).

against overreliance of a common industry modeling approach that may fail to pick up critical negative implications of the scenarios. Clearly, the stress-testing exercise is becoming more institutionalized as an important ongoing regulatory tool.

Even though the genesis of the current focus on stress-testing in the industry has been in part driven by evolving regulatory requirements, increasingly bank senior management have responded to the changing paradigm by explicitly recognizing it as a critical part of the risk management function. Many banks have expanded their stress-testing exercises beyond the regulatory mandates to also gain important strategic risk management insights to evaluate and understand the “worst-case” or “nightmare” scenarios utilizing concepts like reverse stress-testing. The concepts of stress-testing are also feeding into an institution’s economic capital needs under various scenarios, product pricing, as well as determination of risk appetite at the strategic level. Banks continue to invest heavily in the underlying ingredients of stress-testing: internal and external data, and models to implement and analyze the stressful scenarios.

Industry efforts on stress-testing

The focus on stress-testing is a global endeavor for the industry, with banks across the world investing in improving and building out their stress-testing efforts. A recent survey of global financial industry covering 75 large banks and insurance companies across 38 countries by EY/IIF confirmed a significant ongoing effort across the industry in recent years on creating and implementing new stress-testing methodologies.

Unique challenges of stress-testing models

The evolving model governance doctrine⁵ stresses the importance of aligning modeling choices and methodological options with the business purpose of the model. For stress-testing models, the purpose is to produce outcomes not under average or normal business conditions, but under extreme or boundary conditions. This implicit requirement challenges the traditional or conventional wisdom in modeling, where analysts seek to mimic the long-term average expectations when building models. Any model that adequately captures the long-term or average

trends and also builds in the average asset value correlations will often fail to pick up the likely impact under stressful conditions. Put differently, the steady state models need to be designed to produce good predictions over the long-term under normal business and market conditions, whereas the stress-testing models need to capture the rare 1 in 10-, 50-, or a 100-year event. The modeling choices may not be the same for the two objectives articulated above, and this key distinction forms the basis of the authors’ argument for a differential modeling approach between the steady state and stress-testing modeling.

To illustrate this point, it is instructive to consider a hypothetical mortgage portfolio and its evolution across the recent financial crisis. The implications of economic changes on a real estate related portfolio are insightful as the impact of home price movements and their impact on mortgages have become better understood since the U.S. market endured its implications in the recent crisis. A model developed on historical experience in the U.S. covering the pre-2007 period would invariably emphasize the importance of credit history as an important driver of a mortgage portfolio performance. In relationship to the role of asset values or loan-to-value (LTV), credit history typically emerged as the predominant predictor of default during the period of rising home values. However, the relationship switched during the crisis when LTV became the dominant driver of mortgage default as home prices started to decrease, and even mortgage holders with good credit started to default once they realized that the value of their property had fallen well below their outstanding mortgage balance (referred to as strategic default). Similar anecdotes may be found in a host of other portfolios as well, where models based on long-term data and trends fail to pick up the anomalous behavior patterns during a period of crisis or upheaval. Consequently, a robust model that captures the dynamics of any portfolio in the long-term and has immense value in predicting outcomes in a steady-state economic environment may fail to capture the likely outcomes in a stressful period. For example, some institutions have re-estimated their mortgage model after the crisis, updating the parameters to include the implications of macro-economic data such as the home price index and unemployment to account for the downturn, but also used the data prior to and after the downturn to train their model. They evaluated the efficacy of their updated models by recasting the actual economic environment from 2007-2008 period to estimate the projected losses estimated by the model.

⁵ In the U.S., primarily spurred by the joint regulatory guidance issued by the Federal Reserve and the Office of Comptroller of Currency in April, 2012 (FRB SR 11-7 and OCC Bulletin 2011-12 respectively).

Not surprisingly, the models generally fail to account for the magnitude of the actual losses incurred during the financial crisis by a significant amount, primarily because they are not capturing the changing consumer behavior that became evident during the crisis and the degree of cross-correlation across regions with falling home prices (higher asset value correlations than average). Both of these patterns manifested themselves only in the recent housing market collapse and could not have been predicted using a long-term or steady state economic data. Such anomalies also occur in other non-mortgage portfolios as part of the CCAR exercise, where recently developed methods/models fail to produce the level of losses that occurred in the crisis even under particularly stressful scenarios. While the above illustration is loss-centric, similar modeling challenges exist when projecting revenue or balance sheet elements under stressful circumstances.

The above discussion produces a dilemma for banking institutions when developing stress-testing models. On the one hand, they need to use historical data to train, parameterize, and validate their models, but on the other hand they need to ensure that the models are designed so as to pick up the sensitivities that will only emerge in a rare stressful environment. The obvious conclusion being that a good stable model that produces robust estimates in the long-run may not necessarily be a reliable stress-testing model.

Designing stress-testing models

As discussed earlier, a significant challenge exists in building and designing stress-testing models in that the business use of such models may require a significantly different approach than the standard modeling methods that focus on using long-term data to build models with robust predictive powers in the steady state circumstances. However, unlike models designed for the steady state it is clear that stress-testing models need the predictive capability to estimate the boundary conditions or the tail events around the normal or steady state. The first consideration that an institution needs to address is, therefore, whether the stress-testing model should simply extrapolate the predictions from business-as-usual steady state models, or, alternatively design and develop stress-testing models specifically to capture the tail events. Having struggled with the ability of their models to pick up the stressful environment, many banks are moving in the direction of considering developing specific models for stress-testing purposes alone.

An argument can be made that given the limitations of an empirical model discussed above and the need to think about capturing non-historical trends in the analysis, whether a purely judgmental approach to stress-testing may be appropriate. In many instances where portfolios reflect idiosyncratic patterns, it is indeed desirable to consider expert judgment approaches to capture such unique outcomes. However, the use of judgment is not the panacea for designing stress-testing models as qualitative inputs are difficult to validate and justify. If anything, more judgment will necessitate more substantiation and support to authenticate the use of the qualitative model. Nevertheless, in the discussion that follows we will consider a purely qualitative or an expert judgment approach as a model, where a model is defined broadly as a framework.

Based on the evolving industry practices, we offer the following suggestions in designing stress-testing models. For purposes of the discussion below, we assume that stress-testing models specifically include macroeconomic factors as drivers of portfolio dynamics, or in other words, the outcome of these models is influenced by these factors. Further, we abstract from other modeling decisions, such as the underlying lag structure of the timing of the macro impact, and assume that standard modeling methods are employed to ascertain those. Additionally, the discussion is agnostic to the type of model used (loan-level, panel, time series model, etc.). Some of the following considerations challenge the conventional wisdom on acceptable modeling practices.

The most general formulation of the problem may be represented mathematically as:

- (a) $y_{ss} = \alpha + \beta_{ssx} + \epsilon$, where y is the outcome variable and x represents a vector of portfolio and macro-economic factors, estimated under a steady state (SS) or long-term environment. β_{ss} represents the estimated relationship between y and x .
- (b) $y_{st} = \alpha + \beta_{stx} + \epsilon$, where y is the outcome variable and x represents a vector of portfolio and macro-economic factors, estimated under a stressed (ST) environment. β_{st} represents the estimated relationship between y and x under stressful conditions.

The discussion below focuses on estimating β_{ST} in so far as there is a reason to believe that $\beta_{ST} \neq \beta_{SS}$. Some of the specific suggestions include:

Combining business insights into modeling: given the unique business use of the stress-testing models, conduct a pre-development feasibility exercise to evaluate the data, judgment, potential methodology choices, and likely risks and limitations of alternative approaches. Unlike the usual steady state modeling approach, where the business lines outsource the modeling exercise to a quantitative group within the institution that uses the data provided to develop a model based on the agreed-upon specifications, stress-testing requires much more thought and business line input in designing a model that is able to capture portfolio dynamics in an abnormal or an extreme period. This approach also forces the business line to critically evaluate the stressed circumstances and the degree of adverse consequences under such scenarios, making them more resilient if such an event were to materialize. Consequently, it is very important that the business insight into how the portfolio would react under stressful conditions is embedded in the model rather than simply reliant on historical data. This collaborative approach between modeling and business area is critical for determining how much judgment may be required in the process, what is the appropriate time period to cover the stressful environment, and determine the optimal modeling choice.

Parsimonious modeling: another fundamental difference between developing a stress-testing versus the steady state model is the need to build a more general model for stress-testing purposes such that the model can accommodate a wide variety of environments and not be tailored or fitted to a particular set of conditions. Usually, one of the goals in developing a steady state model is to fit it to the long-term data and produce model specification with the highest predictive abilities – for example, Basel II rules require a minimum of 5 years of data to develop credit risk models for retail exposures. However, in building a stress-testing model care should be taken not to fit or “fine tune” the model to a certain data period as the primary purpose of the model is to estimate portfolio behavior in a non-normal environment. Thus, a more general or parsimonious approach is more useful when designing a stress-testing model as it would be less tied to a particular data environment. The modeling community, therefore, has to balance the need between the

stress-testing model's predictive capabilities against the more general and adaptable abilities of the model. Using a minimal set of predictors would produce a model which is better suited in the context of stress-testing models, as the model offers more degrees of freedom to adapt to different economic and market scenarios, a requirement which is at the core of the stress-testing principles. Clearly, such a model would not be as predictive as a model with additional variables fitted to a dataset over the longer horizon, but likely to perform better during the turns in a business cycle. Generally, modelers are trained to optimize on goodness-of-fit metrics where the model specifications with the best fit are selected, but designing a stress-testing model requires a constrained optimization exercise where the modeler deliberately selects a sub-optimal solution from a goodness-of-fit perspective, and favors a parsimonious and general structure.

Parameter selection using outer confidence intervals: most modeling exercises rely on the principle of maximum likelihood or least squares estimation techniques to estimate the parameter values of the explanatory variables at the central tendency or mean of the distribution. As opposed to a judgmental determination of which variables to select, some modelers may prefer to rely on an empirical approach, but instead choose the model parameters not around the mean but outer confidence intervals to recognize the 1 in 10- or a 100-year event. In theory, assuming a rich dataset with sufficient observations, it may be argued that rather than selecting parameter values for a variable that predicts the mean, for stress-testing models it may be more appropriate to consider parameter values at ± 1 standard error (commensurate with outcomes likely to occur only 1/3 of the time), or ± 2 standard error (commensurate with outcomes likely to occur less than 1 in 20+ years). The benefit of this approach is that it is empirically driven but the parameter values represent the outer limits of likely occurrences. The approach is consistent with the empirical analyses that form the basis of most modeling exercises, except by design it specifically considers the less probable outcomes. In effect, the standard errors around a model's estimated parameter value represent a distribution of likely values that those parameters may assume with the mean of the distribution indicating the most likely value, and lower probable outcomes with parameter values as you move away from the distribution mean in both directions. In this approach, parameter values at the tail that produces higher losses or lower revenue (depending on the nature of the model) may be

selected as the stress-testing parameter value for each variable. For example, for a credit loss model, the model developer may choose parameter values at 1 standard error towards the higher losses for each parameter. In modeling terms, making the distinction between β_{SS} and β_{ST} such that the stress-testing model parameters specifically take into consideration the basic purpose of the model to estimate outcomes away from the mean.

Conditional estimators: one criticism of using parameter values at some outer confidence intervals is that the outer tail may not represent different economic environments but rather the simple noise in the data, which can come from a single and stable economic environment. The inability of the previous approach to disentangle the effect of different economic conditions may be addressed by specifically identifying periods of historical stress or downturn, and then producing a number of estimators separately for each downturn period. For example, banks with sufficient historical data may pick recessionary periods corresponding to the recessions in early 80s, 91-93, 2001 9/11, and 2007-2009. For each of these time frames, a separate estimate may be generated: β_{ST1} , β_{ST2} , β_{ST3} , and β_{ST4} , corresponding to each of the previous recessionary periods. For purposes of stress-testing, either the bank may use specific historical experience that is closest to the future scenario, or use the multiple points to develop a distribution of parameter values under stressful times to compute a $\hat{\beta}_{ST2}$ from that distribution as any metric that measures the central tendency of that distribution. For many institutions, lack of sufficient historical data may limit their ability to execute this approach.

Event study approach: recognizing that the lack of data around economic downturns may limit a bank's ability to robustly estimate their conditional estimators, and furthermore not all recessionary periods are sufficiently long enough to estimate a reasonable model. One strategy could be to combine the entire dataset over the long horizon, but use additional indicator variables to tag periods of down-turn (which may be as little as a few months in some instances), and then estimate the model to compute the β_{ST} as an interaction term with the tagged common downturn variable. This method is conceptually very similar to the conditional estimator approach described above but uses a different implementation approach to estimate the mean β_{ST} . The approach also presents some flexibility in estimating parameters across the different time periods in a business cycle.

Reversion to a pure optionality assumption under stress:

another approach to build-in the stress-testing elements into a model is to redefine the model and limit it to a pure option-theoretic framework. In other words, the obligor "put" option is the only consideration for a stress-testing framework, while many other aspects are evaluated in the steady state model for the same portfolio and purpose. In the mortgage example discussed earlier, the pure optionality would suggest that the only factor that should be considered is the borrower's loan-to-value and should the home value drop below the outstanding loan amount, the borrower will ruthlessly exercise his option to default. Similarly, while for a C&I portfolio, a bank may utilize a rich set of rating scorecards by industry sector in a steady state environment, an obligor may exercise their put option to default when the value of the collateral drops below the loan amount, or the rent from an income-producing asset falls below the debt service levels, both of which optionalities are typically not explicitly captured in the scorecards. Similar extensions of the ruthless put option view may be utilized for the loss exposure models for stress-testing purposes ignoring other elements that are typically considered in steady state conditions.

As a practical matter, banks may choose a hybrid approach combining elements from multiple considerations presented above to suit the specific needs of their specific portfolios. However, the key is to recognize that alternative methods, adjustments, assumptions, and judgments may be necessary when it is clear that $\beta_{ST} \neq \beta_{SS}$. Furthermore, some banks may choose to continue using the traditional steady state models for stress-testing as their core methodology, but supplement the analysis of the associated risks and limitations of those steady state models using some of the considerations suggested above. For example, the potential model risk of a long-term model used for stress-testing may be quantified using the "event study" or pure "option" approach, such that the bank may be able to use that to ensure adequate capital buffer for model risk. When it comes to stress-testing models, every bank faces a unique set of challenges, be it data, resources, materiality of the portfolio, and so on – all of which will determine the appropriate modeling strategy for that institution. The term model strategy is used to emphasize that no one modeling approach may suffice, but a combination of different methods may be necessary to produce a core estimate of the future scenarios which needs to be coupled by either corroborative methods to support that conclusion,

or alternatively measure model risk associated with the core estimate. Either way, it is critical to think beyond the traditional modeling methods when designing the modeling strategy for stress-tests.

Governance of stress-testing models

A fair question may be raised in the context of different unconventional strategies discussed earlier as to how the “independent validation” team can validate the myriad of approaches suggested in the previous section. Most model validation groups are geared towards evaluating empirically-driven models using standard or commonly accepted modeling methods. The recent regulatory guidance emphasizes the role of back-testing as a fundamental basis for model risk guidance as well.

The key point to address this dilemma is that model governance does not equate to back-testing alone. If one looks at the period prior to the financial crisis, one finds that most institutions were using models that had been back-tested on a routine basis, producing very standardized validation reports. So much so that there was a significant trend among banks to off-shore model validation functions under the premise that back-testing is a repeatable compliance exercise requiring minimal oversight. Yet, even with frequently back-tested and compliant models, which is akin to looking in the rear view mirror, those models faced credibility questions at the onslaught of the financial crisis. Stretching the analogy, even though banks were equipped with spotless rear view mirrors, few had the tools to look beyond the curve in the road ahead. We argue, therefore, that the key to effective model governance is to focus on “effective challenge” as the primary tool to manage model risk, as opposed to singular concepts such as back-testing. The need for effective challenge is arguably the single biggest theme of the recent regulatory guidance on model risk management as well – the guidance specifically includes processes with qualitative inputs but producing quantitative outputs as being within the definition of a model. The considerations for stress-testing models to better align the model output with realistic stressful scenarios would be within the bounds of model risk management, albeit different types of skills may be necessary to apply effective challenge to such models.

The governance of a stress-testing-model involves a much more holistic assessment of the model than mere back-testing. It has to take into consideration the model design, its adaptability to different economic conditions, sensitivity to changing environment, reasonable benchmarking to alternative methodologies, and appropriateness of model outputs. The need for diverse approaches to estimate stress models is imperative as it provides a benchmark for what may happen under extreme conditions from multiple methodological perspectives. The worst outcome from this initiative would be if everyone converges to one standard view for modeling the future extreme conditions, and the obvious fear is that if that approach fails to pick up a turn in the cycle we would be no wiser than we were going into the last recession. Consequently, prudent model governance requires that senior bank management challenge the stress-testing model methodologies sufficiently, and not accept the absolute outcome of such models without questioning the model's ability to pick up changing business environments or comparing their output against some reasonable benchmarks, including expert judgment for corroborating the output. It will never be possible to back-test or “validate” the stress-test model predictions, unless the extreme conditions materialize with sufficient frequency to reach such conclusions. The management, therefore, needs to focus more on understanding the risks and limitations of such models to formulate their view of how the model will perform in adverse conditions, even if such views are based on a qualitative assessment of the models.

Conclusion

Stress-testing models form the basis for evaluating a bank's performance, capital position, and sustainability under a stressful environment, and are designed to serve as the proverbial "canary in a coal mine." As stress-testing becomes an ever more critical component of risk management, given the recent industry experience through the financial crisis, it becomes important that senior management develop confidence and comfort with the bank's stress-testing models. The most important aspect of these models is that by design, they are not, and should not, resemble the long-term steady state models that are used in so many applications within the bank to project likely or average outcomes. Instead, these models should try to focus on capturing the extreme events. The design and governance of such models has to keep that important purpose in the forefront, which requires a significant amount of qualitative and quantitative adjustments.

It is critical that senior management through its review and challenge process gain adequate insights into the risks and limitations of stress-testing models in order to develop confidence in the model output, and be in a position to make any qualitative adjustments to the output as these models will continue to serve important strategic business imperatives.

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