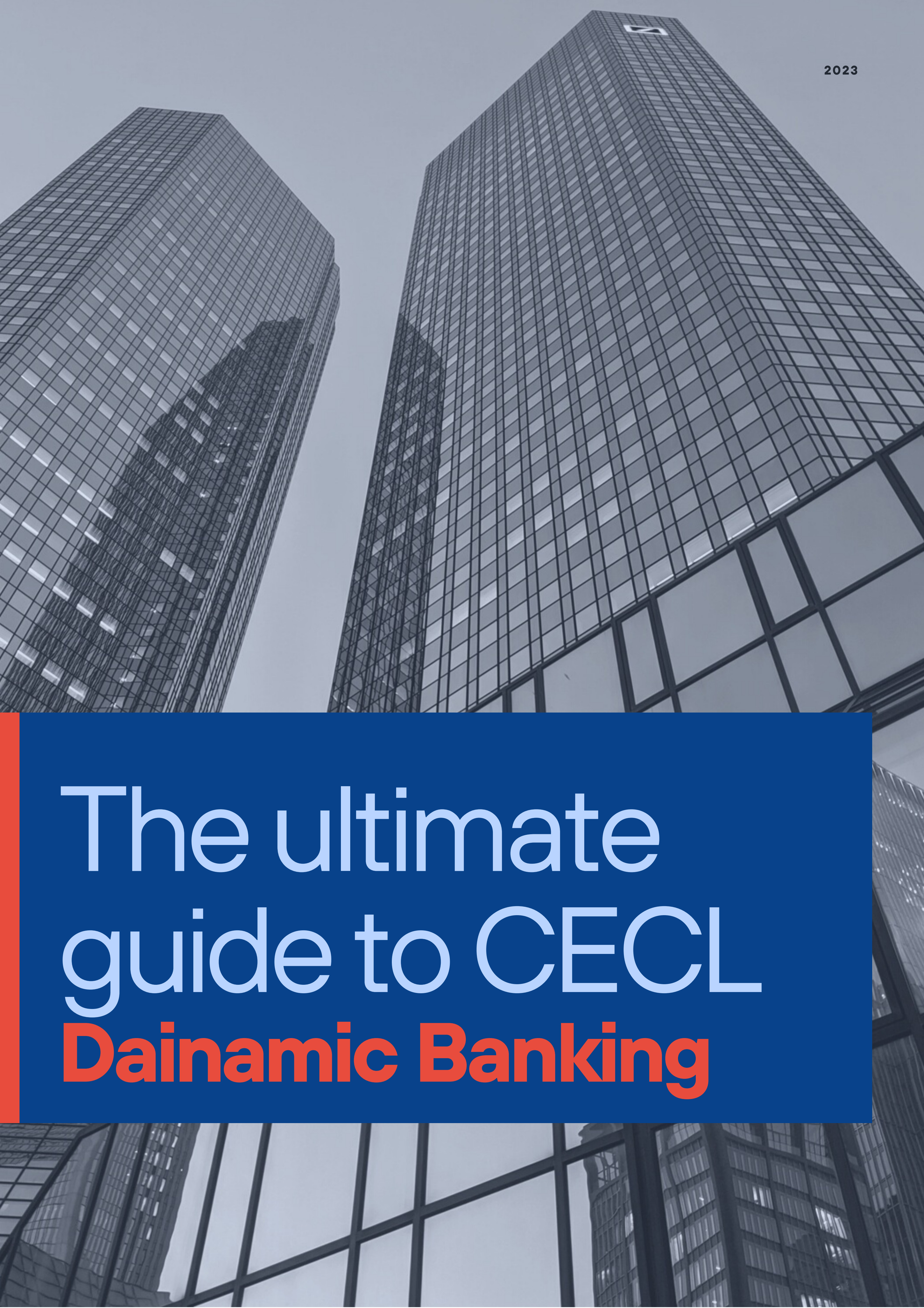

2023

The ultimate guide to CECL

Dainamic Banking

Dainamic Guidelines for **bankers and CECL**

THE ULTIMATE GUIDE TO CECL

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Executive Summary

The Financial Accounting Standards Board (FASB) under the Accounting Standards Update (ASU) No. 2016-13 required financial institutions to implement the Current Expected Credit Losses (CECL) methodology for estimating credit losses. An important part of the CECL implementation is the maintenance of a comprehensive and detailed audit trail.

The new approach with CECL contrasts with the incurred loss in three ways:

- Timing of Loss Recognition
- Forward-Looking Information
- Loss Horizon

Timing of Loss Recognition - Whereas losses were recognized only when they were likely, or "incurred," now financial institutions are required to estimate expected losses over the life cycle of a loan regardless of whether a trigger event has occurred.

Forward-Looking Information - Whereas historical loss rates were used to calculate allowances, now financial institutions must produce “reasonable and supportable” forecasts about future economic conditions and take a forward-looking approach.

Loss Horizon - Whereas losses were estimated over a relatively short period, expected losses must now be computed over the contractual life of a loan.

These changes reflect a substantial increase in the complexity of the modeling capabilities and data requirements, which disproportionately affects smaller banks because they typically do not have full-time analytics, data science , and legal teams that can absorb the new regulatory burdens. However, institutions that only view CECL as a new regulation to comply with will be at a disadvantage, relative to those that view it as an opportunity to cultivate best practices. In particular, CECL reflects a step towards more reliable and real-time forecasting of economic activity and risk management, and excelling at these dimensions will help institutions not only avoid crises, but also identify new markets to expand into and better serve existing customers. The purpose of this primer is to explain the major components of CECL compliance with clear action steps and recommendations over how to best adapt and adhere to the requirements.

CECL Model Documentation

As we transition from the incurred loss model to the CECL model, it is crucial to understand the heightened complexity and specificity required in our model documentation.

Under the incurred loss model, we primarily based our loss estimates on historical loss rates, focusing on loans that showed evidence of a trigger event. The documentation required for the incurred loss model reflected this relatively straightforward approach – simply reporting a trigger event on a loan.

However, CECL requires that banks estimate losses at the time of origination or purchase, incorporating forward-looking information, and considering the life of the loan, demanding a more comprehensive and detailed approach to our model documentation, including:

- Model Description - This would be a detailed explanation of the model's logic and structure. This includes the specific type of model used (such as logistic regression, survival analysis, or a machine learning model), as well as a description of how the model processes inputs to produce estimates of expected credit loss.

- Underlying Assumptions - While every model is built on a set of assumptions, some assumptions will be easier to defend than others, e.g. that certain economic conditions are associated with greater degrees of losses. By analyzing historical data and using statistical models, assumptions can be tested. Nonetheless, even untested assumptions should be clearly stated and their significance communicated with sensitivity tests.

- Methodology - This would include a detailed description of the statistical methodology used for estimating expected losses, such as the estimator and features used.

- Data - A clear description of the data used in the model is crucial. This includes the source of the data, the specific variables used, any data cleaning or preprocessing steps, and any data validation procedures. While you may choose to use only your own data, and that should be made clear if so, you may also find it useful to use external data on comparable banks from the Call Reports or other local economic data.

- Parameter Selection - Ever model involves parameters (e.g., the weights in a logistic regression model), requiring an explanation for how these parameters were chosen . You may simply explain the type of regression method you are using and how you are evaluating model fit and the choice of features included in the model.

- Model Validation - You should provide evidence of ongoing model validation. This could include out-of-sample testing (where the model's predictions are compared to actual outcomes for data that was not used in training the model), back-testing (comparing the model's predictions to actual historical outcomes), sensitivity analysis (checking how much the predictions change with small changes in the inputs or parameters), and stress testing (seeing how the model performs under extreme but plausible conditions). A major and common shortcoming is failure to test for out-of-sample fit, which is especially important for CECL since forecasts that end up being very inaccurate will damage credibility with regulators down the road (and stifle internal decision-making).

Economic Forecasts

Transitioning to the CECL fundamentally changes how we incorporate economic conditions into our credit loss estimates.

Unlike the incurred loss model, which relied on historical loss data and less explicitly on future economic conditions, the CECL model necessitates a proactive and comprehensive consideration of future economic scenarios.

Under the incurred loss model, losses were recognized based on evidence of a trigger event, and thus economic forecasts played a less critical role. However, a CECL model requires that institutions forecast expected losses over the life of a financial instrument, demanding forecasts of future economic conditions and their impact on the portfolio. As a result, forecasts must detail the economic scenarios, including the rationale for their selection, the association between these conditions and credit losses, and the duration of the "reasonable and supportable" forecast period. Beyond that period, institutions can revert to a historical credit loss standard.

- Selection of Economic Scenarios - Every institution must articulate a set of "reasonable and supportable" forecasts that are used in model building, including at least one base case scenario, as well as adverse and severely adverse scenarios. The rationale for their selection should be clearly explained, along with their sources (i.e., original forecasts are not required). Qualitative factors can also be manually incorporated.

- Association with Credit Losses - Since a major part of CECL is characterizing how changes in economic conditions affect expected credit losses, a detailed explanation of how various economic factors (e.g., GDP growth, unemployment rates, and interest rates) influence credit losses in the model is important to have. If qualitative factors are also included in the model, then there must be an explanation of how they are applied to the estimates. For example, if a bank has tightened its lending standards, it might look at the effect of past tightening episodes on default rates. In other cases, the relationship might be more speculative, and the institution will have to rely on expert judgment.

- Reasonable and Supportable Forecasts - CECL requires evaluating economic conditions over the contractual life of the financial instruments, which means building "reasonable and supportable" forecasts. The length of this period can vary depending on the nature of the financial instruments and the availability of economic forecasts.

- Reversion Method - For periods beyond the 'reasonable and supportable' period, CECL requires a reversion to historical loss information (since any forecasts would require more heroic assumptions). The methodology and timing for this reversion should be disclosed, along with the historical loss information used.

- Modeling Assumptions - All assumptions made in the economic forecasting process should be clearly documented. This includes any assumptions about the relationships between economic variables, or between economic variables and default rates. For example, a statistical relationship that holds in some years may vary in other years; such an assumption should ideally be tested, but at least communicated if no alternative exists.

Importantly, users can borrow forecasts from published studies or other internal deliberations. However, the downside to taking off-the-shelf estimates is that they fail to take into account the context and relevant customization of the composition of borrowers for any given institution. That can lead to institutions receiving direct or indirect penalties associated with CECL by committing to overly stringent capital reserve ratios and/or accounting for inaccurate or less relevant forecasts that adversely affect decision-making. As a result, an institution may choose to build its own forecast by drawing upon its own data coupled with external data.

Risk Management Process

Under the incurred loss model, our risk management focused primarily on identifying and measuring losses that had already been incurred.

However, the CECL model requires us to estimate expected losses over the life of a financial instrument, necessitating a proactive and comprehensive risk management process. The updated risk management process must encompass robust procedures and controls, a clear governance framework, a thorough understanding of the model by senior management, rigorous model validation procedures, and stringent audit protocols. Moreover, every aspect of the risk management process should be carefully documented, ensuring that the approach to credit loss estimation under CECL is not only rigorous and systematic, but also transparent and accountable.

- Procedures and Controls - Your institution should have a set of procedures and controls to ensure the accuracy and reliability of your CECL model. These might include regular checks of the data used in the model, protocols for updating the model when necessary, and controls to prevent or detect errors or fraud. Any manual entry or analysis should be flagged and double checked to avoid potentially large errors from propagating.

- Model Governance Framework - The governance of the CECL model should be clearly defined, including who is responsible for the model, how decisions about the model are made, and how those decisions are reviewed and approved. The governance framework should also outline the responsibilities of the board and senior management. Analysts involved in building, operating, and revising the model should also be disclosed.

- Understanding of the Model - The board and senior management should have a good understanding of the CECL model, including how it works, its limitations, and the key assumptions it makes. They should also understand the potential impact of the model on the institution's financial statements and capital position.

- Model Validation - Institutions should test their model out-of-sample, which involves estimating the model on a subset of data and using the estimated parameters to forecast what would happen in the subset of the data that was held out from estimation. This process is referred to as “cross validation” in computer science and takes many forms, but effectively it just ensures that any statistical model is not over-fitting the data in-sample.

- Audit - Institutions should review the model documentation, check the procedures and controls, and assess the model governance framework. The documentation should be detailed enough to allow an outsider to evaluate and understand the model. In many ways, the processes should resemble a product requirements document.

Regulators often are more interested in the process, transparency, and understanding among the institution’s senior management than any specific number per se. There are ongoing debates among reasonable people about specific statistical strategies and processes for producing reliable forecasts, but a well-documented, replicable, clear, and transparent process signals to regulators that risk is understood and managed.

Dainamic Banking's Recommendations

Based on the growing complexity of regulatory compliance and the necessity of producing reasonable, and supportable forecasts of real-time credit risk, there are a couple of immediate next steps to consider to best position yourself as a financial institution.

Recommendation #1: Identify your peers and let their data inform your model building
Nearly all of the existing CECL solutions draw on national data, ranging from GDP growth to unemployment to delinquencies, to inform their forecasts. However, what is going on in the nation as a whole is not necessarily relevant for an individual bank – especially a small or mid sized bank that lends in a specific area. By drawing on data among actual peers, whether by geography or assets under management (or both), your financial institution will not be penalized for any adverse events going on in the nation as a whole – focus on what you can control.

Recommendation #2: Decide the level of sophistication you think is needed for your forecasts
Different sizes of institutions have different requirements. For example, a small bank with under $500 million in assets under management poses no systemic risk to the financial system, meaning that there is less scrutiny in the eyes of a regulator, particularly relating to times of national turbulence. By focusing on local and peer historical data, small banks can learn from the past without having to deploy extremely complicated machine learning models for predicting future losses and economic activity.

Recommendation #3: Consolidate relevant data that would be used in forecasts and explore how to combine external and internal data to improve model predictions.
The revolution in machine learning has been fueled by the emergence of large-scale data and increased computing power. Furthermore, more and more data is becoming accessible, ranging from the Call Reports data on bank balance sheets to the Quarterly Census of Employment and Wages on county labor market indicators. To realize gains in forecasting model reliability, these disparate sources of data must be combined and mined jointly. Institutions should consider augmenting their internal data with external data to realize the greatest mileage.

Recommendation #4: Test simple models and confirm the basics are working properly
While it is tempting to run for the more sophisticated models, a major lesson in data science is starting with the simplest model to ensure that the data pipeline and model are working as they should before estimating a more complicated specification. Furthermore, many smaller banks do not need complicated solutions. For some, they simply need historical data on their peers to conduct basic time series analysis to derive a general trajectory of growth across asset classes (i.e., running linear regressions and carefully extrapolating).

Recommendation #5: Run a comparison between different models and present one as a supplement for regulators
We are still in the early days of CECL regulation and compliance. Even the regulators are still finding their way and modeling is difficult to begin with. Given the emphasis on transparency in CECL compliance, experimenting with different modeling approaches and presenting a range of estimates can help reduce risk and also provide a forum for critical inquiry into the modeling approach that best serves the institution.

Endnotes

1. The Interagency Policy Statement on Allowances for Credit Losses and the Interagency Guidance on Credit Risk Review Systems explains that an audit trail should provide a historical record of all activities and actions related to the CECL process. It should ensure transparency, accountability, and traceability of decisions, supporting the integrity of the process and allowing for review by internal auditors, external auditors, and regulatory examiners. The components of a robust audit trail include clear documentation of all actions and decisions related to the CECL process, the identification of individuals involved, a record of changes over time, and the preservation and accessibility of records.

2. In fact, that is one reason why, during the height of the financial crisis, many banks did not realize losses on delinquent and borderline foreclosed mortgages – doing so would have put many bank balance sheets underwater and into insolvency; see, for example, Makridis, C. A., and Ohlrogge, M. (2023). The Local Effects of Foreclosure, Journal of Urban Economics, Review and Resubmit.

3. Under the CECL framework, financial institutions are expected to estimate the expected credit loss for each major asset class on their balance sheet. This includes various types of loans (such as mortgage loans, auto loans, commercial loans, etc.) and investment securities, among other financial instruments. Each of these asset classes can have different risk characteristics and may behave differently under various economic conditions. The key is to have a reasonable and supportable basis for the loss estimation model for each asset class. For example, the factors influencing the likelihood of default and loss given default may be different for a commercial real estate loan compared to an auto loan.

4. Qualitative factors can include a wide range of variables that might affect credit losses but are not captured in the historical data, including, for example: changes in lending policies and standards, changes in economic or business conditions, changes in the nature or volume of the portfolio, changes in the experience, ability, or depth of lending management and staff, and changes in the volume or severity of past due, classified, or non-accrual assets, among others. If qualitative factors are used, there must be a well-defined and systematic process for identifying them so that they do not look cherry picked.

5.When estimating expected credit losses, institutions must consider not only past and current conditions, but also future economic conditions over the contractual life of the loan or financial instrument. For example, if a loan is set to mature in five years, the institution needs to consider how the economy might change over those five years and how those changes could affect the likelihood of the borrower defaulting. The forecast for these future economic conditions should be "reasonable and supportable," which means the institution should use all available information to make the best possible estimate of future conditions. That can include, but does not need to, formal quantitative models. An additional feature of the “reasonable and supportable” requirement for forecasts is the recognition that the further the projection is in the future, the greater the uncertainty. As a result, the life cycle of a loan should be specified and the forecast should only go up to the period that is supportable. For periods beyond the "reasonable and supportable" period, institutions revert to historical loss information. In other words, they should assume that the risk factors revert to their long-term averages. This allows the institution to still consider the full life of the loan, even if detailed forecasts are not available for the entire period.

ABOUT DAINAMIC

OUR MISSION

Empowering financial institutions with sophisticated computational methods powered by artificial intelligence and regulatory compliance solutions, our mission is to level the playing field in risk management and strategic decision-making, especially for small and regional banks, driving stakeholder value even in uncertain economic landscapes.

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Christos holds dual doctorates and masters in economics and management science & engineering from Stanford University with over 80 peer-reviewed research papers, over 200 stories in the media, and holds academic and faculty appointments at Stanford University, Columbia University, University of Nicosia, among others.

Christos previously served on the White House Council of Economic Advisers and as a non-resident fellow at the Harvard Kennedy School of Government and MIT Sloan. He continues to advise organizations and governments.