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STRESS TESTING

OPERATIONAL RISK

TECHNOLOGY & INNOVATION

LIQUIDITY

CECL / IFRS 9
Section 1: Introduction

In the United States, the Financial Accounting Standards Board ("FASB") issues the set of standards known as Generally Accepted Accounting Principles ("U.S. GAAP"), a common set of guidelines for the accounting and reporting of financial results. In this we focus on the guidance governing the Allowance forLoan and Lease Losses ("ALLL"), the financial reserves that firms set aside for possible credit loss on financial instruments. The recent revision to these standards, the Current Expected Credit Loss ("CECL"; FASB, 2016) standard, is expected to substantially alter the financial results. In this section, we discuss some of the practical challenges facing institutions in implementing CECL frameworks.

The recent revision to these standards, the Current Expected Credit Loss ("CECL"; FASB, 2016) standard, is expected to substantially alter the financial results.

This paper will proceed as follows. In Section 2, we will discuss some practical challenges faced by the industry in establishing models and processes to meet CECL requirements, and in Section 3, we will summarize an empirical analysis of the impact of assumptions on CECL estimates.

Section 2: Practical Challenges in Implementing CECL

In this section, we discuss some of the practical challenges facing institutions in implementing CECL frameworks. In the midst of the financial crisis during 2008, when the problem of counter-cyclicality of loan loss provision came to the fore, the FASB and the IASB established the Financial Crisis Advisory Group to advise on improvements in financial reporting. This was followed in early 2011 with the communication by the accounting bodies of common solutions for impairment reporting. In late 2012, the FASB issued a proposed change to the accounting standards governing credit loss provisioning (FASB, 2012) which was finalized after a period of public comment in mid-2016 (FASB, 2016), while in the meantime the IASB issued its final IFRS 9 accounting standard in mid-2014 (IASB, 2014). The IFRS 9 standard was effective as of January 2018 while CECL is effective in the U.S. for SEC registrants in January 2020 and then for non-SEC registrants in January 2021; however, for banks that are not considered Public Business Entities (PBEs), the effective date will be December 31, 2021.

The new standard will be effective for banks that are not considered Public Business Entities (PBEs), the effective date will be December 31, 2021.

Figure 2: The accounting supervisory timeline for CECL and IFRS 9 implementation

Figure 3: The CECL accounting standard – Regulatory Overview

FASB Proposed Changes

A. Accounting Classification

B. Impairment - Measurement of Credit Losses on Financial Instruments

C. Implementation and Disclosures

Legend

Regulatory Milestones (Past)  Regulatory Milestones (Indicative)
In Figure 3, we depict some high level overview of the regulatory standards and expectations in CECL. The first major element, which has no analogue in the legacy ALLL framework, is that there has to be a clear segmentation of financial assets, into groupings that align with portfolio management and which also represent groupings in which there is homogeneity in credit risk. This practice is part of traditional credit risk modeling, as has been the practice in Basel and CCAR applications, but which represents a fundamental paradigm shift in provisioning processes. Second, there are changes to the framework for measuring impairment and credit losses on financial instruments, which has several elements. One key aspect it enhances data requirements for items such as Troubled Debt Restructuring ("TDRs") on distressed assets, and lifetime loss modeling for performing assets. This will require a definition of model granularity based on existing model inventories (i.e., Basel and CCAR), data availability and a target level of accuracy. Moreover, this process will involve the adoption of new modeling frameworks for provision modeling. Finally, institutions will face a multitude of challenges around implementation and disclosures. This involves an enhanced implementation platform for model and reporting (e.g., dashboards), as well as revised accounting policies for loans and receivables, foreclosed and repossessed assets and fair value disclosures.

**Figure 4: Key business impacts of the CECL Accounting Standard**

- **Business Impacts**
  - Significant increase in the ALLL of 25-100%, varies based on portfolios
  - Potential reclassification of instruments & additional data requirements for lifetime loss calculations
  - Additional governance and control barriers due to new set of modeling & implementation frameworks
  - More frequent consolidation of modeling and GL data, as well as results from multiple sources
- **Operational Impacts**
  - Enhanced reporting of the ALLL and other factors
  - Increased operational complexity due to augmented accounting requirements
  - Additional modeling and other resources required to support modeling, risk reporting and management
  - Alignment between modeling and business stakeholders
  - Operational governance increases for data quality, lifetime calculation, modeling and GL reconciliation
- **Technological Impacts**
  - Increased computational burden for different portfolios (e.g., high process time for Retail portfolios based on granularity, segmentation and selected model methodology)
  - Expansion of more granular historical data capacity
  - Large computational power for frequent (monthly) run of the ALLL estimate
  - Augmented time requirements to stabilize the qualitative and business judgment overlaps across portfolios

In Figure 5, we depict some high level overview of the regulatory standards and expectations in CECL. The first major element, which has no analogue in the legacy ALLL framework, is that there has to be a clear segmentation of financial assets, into groupings that align with portfolio management and which also represent groupings in which there is homogeneity in credit risk. This practice is part of traditional credit risk modeling, as has been the practice in Basel and CCAR applications, but which represents a fundamental paradigm shift in provisioning processes. Second, there are changes to the framework for measuring impairment and credit losses on financial instruments, which has several elements. One key aspect it enhances data requirements for items such as Troubled Debt Restructuring ("TDRs") on distressed assets, and lifetime loss modeling for performing assets. This will require a definition of model granularity based on existing model inventories (i.e., Basel and CCAR), data availability and a target level of accuracy. Moreover, this process will involve the adoption of new modeling frameworks for provision modeling. Finally, institutions will face a multitude of challenges around implementation and disclosures. This involves an enhanced implementation platform for model and reporting (e.g., dashboards), as well as revised accounting policies for loans and receivables, foreclosed and repossessed assets and fair value disclosures.

**Figure 5: Best industry practices in implementing the CECL Accounting Standard**

1. **CECL Regulatory Requirements Analysis**
   - Mapping of CECL requirements to different bank functions and teams
   - Analysis of data sources required for compliance
2. **Gap Analysis and Solution Design**
   - Defining the scope and body of work for the new CECL model methodology
   - Informing and defining the framework for ALLL estimation and the impact on the bank
3. **Model Development**
   - Developing and evolving capabilities for new data requirements and modeling frameworks
   - Developing modeling frameworks for PO term structure, spot LGD & EAD, and lifetime loss calculations
4. **End-to-end Implementation**
   - End-to-end implementation frameworks for CECL, including data, process, workflow, simulation, etc.
   - Consideration of long term sustainability and efficiency
5. **Automated and Standardized Reporting**
   - Defining and designing the reporting framework for regulators and internal stakeholders covering the existing and future views
   - Standardization and automation of the monthly reporting process
   - Executing and end-to-end impact assessment and reporting

**Figure 6: Data considerations and challenges in implementing the CECL Accounting Standard**

- **Data Quality:** significant effort in reconciliation with the General Ledger, missing value treatment, outlier treatment, data validation, and data transformation for CECL models
- **Sufficient number of accounts and defaults:** the requirement to analyze the whole life of the loan, a shortage of sufficient number of accounts for modeling in some portfolios
- **Availability of origination data and origination variable:**
- **Availability of historical as well as forecast of macroeconomic factors - historical values of macroeconomic factors for model building.**
- **Accuracy of multi-year forecast of macroeconomic factors for the calculation of ‘forward looking’ Expected Credit Loss (ECL) estimates**
- **Calculation of ‘lifetime’ for revolving loans**
- **Data Infrastructure - implementation of CECL will require a large volume of high quality data.**

**Figure 7: Modeling considerations and challenges in implementing the CECL Accounting Standard**

<table>
<thead>
<tr>
<th>Areas</th>
<th>Category Considerations / Challenges</th>
</tr>
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<tbody>
<tr>
<td><strong>Segmentation</strong></td>
<td>-</td>
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<td><strong>Criteria</strong></td>
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<td><strong>Data Limitation</strong></td>
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<td><strong>Definition</strong></td>
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<td><strong>Estimation</strong></td>
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<td><strong>Incorporation of forward looking information</strong></td>
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<td><strong>Model Methodology</strong></td>
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**Figure 8: Implementation considerations and challenges in the CECL Accounting Standard**

<table>
<thead>
<tr>
<th>Areas</th>
<th>Category Considerations / Challenges</th>
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<tbody>
<tr>
<td><strong>Data / System Requirements</strong></td>
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<tr>
<td><strong>Credit Metrics</strong></td>
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<tr>
<td><strong>Implementation</strong></td>
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<tr>
<td><strong>Reporting</strong></td>
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The complexity of CECL requirements require the firms to act now, due to tight implementation timelines and large body of work, and put in place a program to understand the overall impact to the firm from a business and technology perspective.

Section 3: The impact of modeling assumptions on CECL estimates: Bench-marking, backtesting and model risk

There are some key modeling assumptions to be made in constructing CECL forecasts. First, the specification of the model linking loan losses to the macroeconomic environment will undoubtedly drive results. Second, and no less important, the specification of a model that generates macroeconomic forecasts and most likely scenario projections will be critical in establishing the CECL expectations. As we know from other and kindred modeling exercises, such as stress testing (“ST”) used by supervisors to assess the reliability of credit risk models in the revised Basel framework (Basil Committee on Banking Supervision, 2006) or the Federal Reserve’s comprehensive capital analysis and review (“CCAR”) program (Board of Governors of the Federal Reserve System, 2009), models for such purposes are subject to supervisory scrutiny. One concern is that such advanced mathematical, statistical and quantitative techniques and models can lead to model risk, defined as the potential that a model does not sufficiently capture the risks it is used to assess, and the danger that it may underestimate potential risks in the future (Board of Governors of the Federal Reserve System, 2011). We expect that the depth of review and burden of proof will be far accentuated in the CECL context, as compared to Basel or CCAR, as such model results have financial statement reporting implications.

In the study of Jacobs (2018), the toward the end of analyzing the impact of model specification and scenario dynamics upon expected credit loss estimates in CECL, the author implements a highly stylized framework borrowed from the ST modeling practice. He performs a model selection of alternative CECL specifications in a top-down framework, using FDIC FR-Y9C (“Call Report”) data and constructing an aggregate average hypothesis bank, with the target variable being the charge-off rate (“NCOR”) and the explanatory variables constituted by Fed-provided macroeconomic variables as well as bank-specific controls for idiosyncratic risk. This study is not only the impact of the ALLL estimate under CECL for alternative model specifications, but also the impact of different frameworks for scenario generation: the Fed baseline assumption, a Gaussian Vector Autoregression (“VAR”) model and a Markov Regime Switching VAR (“MS-VAR”) model, following the study of Jacobs et al (2018).

It is established in this study that, in general the CECL methodology is at risk of not achieving the stated objective of reducing the procyclicality of provisions relative to the legacy incurred loss standard, as across models he observes chronic underprediction of losses in the last 2-year out-of-sample period, which arguably is a period that is late in the economic cycle. Furthermore, this measure of such procyclicality exhibits significant variation across model specifications and scenario generation frameworks. In general, the MS-VAR scenario generation framework produces the best performance in terms of fit and lack of model-under-prediction relative to the perfect foresight benchmark, which is in line with the common industry practice of giving weight to adverse but probable scenarios, which, the MS-VAR-regime switching model can produce naturally and coherently as part of the estimation methodology that places greater weight on the economic downturn.

It is also found that, for any scenario generation model, across specification, the more lightly parameterized models tend to have better out-of-sample performance. Furthermore, relative to the perfect foresight benchmark, the MS-VAR model produces a lower level of variation in the model performance loss predictive model specifications. As a second exercise, the author attempts to quantify the level of model risk in this hypothetical CECL exercise, an approach that uses the principle of relative entropy.

The author finds that, more elaborate modeling choices, such as more highly parameterized models in terms of explanatory variables, tend to introduce more measured model risk, but the MS-VAR specification for scenario generation generates less models risk as compared to the Fed or VAR frameworks. The implication is that banks may wish to err on the side of more parsimonious approaches, but also should attempt to model the non-normality of the credit loss distribution, in order to manage the increased model risk that the introduction of the CECL standard may give rise to.

The implication of this analysis is that the volume of lending and the amount of regulatory capital held may vary greatly across banks, even when it is the case that the respective loan portfolios have very similar risk profiles. Another consequence of this divergence of expected loan loss estimates under the CECL standard is that supervisors and other market participant stakeholders may face challenges in comparing banks at a point in time or over time. There are also implications for the influence of modeling choices in specification and scenario projections on the degree of model risk introduced by the CECL standard.

In this paper, the data is sourced from the Statistics on Depository Institutions (“SDI”) report, which is available on the Federal Deposit Insurance Corporation’s (“FDIC”) research website. This bank data represents all insured depository institutions in the U.S. and contains information on balance sheet and off-balance sheet line items. The study uses quarterly data from the 4th quarter of 1991 through the 4th quarter of 2017. The models for CECL are specified and estimated using a development period that ends in the 4th quarter of 2015, leaving the last 2 years (2016 and 2017) as an out-of-sample forecast. The model development data are Fed macroeconomic variables, as well as aggregate asset-weighted average values of bank financial characteristics for each quarter, the Interest Revenue / Total Net Interest Income ratio over the last 2-year out-of-sample period. The total value bank assets in the system.

The study considered a diverse set of macroeconomic drivers representing key dimensions of the economic environment, and a sufficient number of drivers (balancing the consideration of avoiding over-fitting) by industry standards (i.e., at least 2–3 and no more than 7–9 independent variables). According to these criteria, the author identifies the optimal set focusing on 5 of the 9 most commonly used national Fed CCAR MVs as input variables in the VAR model.

- Unemployment Rate (“UNEMP”)
- BBB Corporate Bond Yield (“BBBCY”)
- Commercial and Industrial Loans Growth Rate (“CDLGR”)
- Trading Account Assets to Total Assets (“TAAAT”)
- Other Real Estate Owned to Total Assets (“OTOTA”)
- Total Unused Commitments Growth Rate (“TUCGR”)

Similarly, he identifies the following balance sheet items, banking aggregate idiosyncratic factors, according to the same criteria:

- Commercial and Industrial Loans to Total Assets (“CILTA”)
- Commercial and Development Loans Growth Rate (“CDLGR”)
- Trading Account Assets to Total Assets (“TAAAT”)
- Other Real Estate Owned to Total Assets (“OTOTA”)
- Total Unused Commitments Growth Rate (“TUCGR”)
The historical data are 65 quarterly observations from 4Q01 to 4Q17 described in Table 1 of the paper. It observes that all correlations have intuitive signs and magnitudes that suggest significant relationships, although the latter are not large enough to suggest any issues with multicollinearity. The author identifies 14 optimal models according to the criteria discussed previously, 7 combinations macroeconomic variables (4 bivariate and 3 trivariate specifications), as well as versions of these incorporating idiosyncratic variables:

- Model 1: Macroeconomic - UNEMP & BBBCY; Idiosyncratic - none.
- Model 2: Macroeconomic - UNEMP & BBBCY; Idiosyncratic - TAAA & CDLGR.
- Model 3: Macroeconomic - UNEMP & CREPI; Idiosyncratic - none.
- Model 4: Macroeconomic - UNEMP & CREFI; Idiosyncratic - TAAA & CDLGR.
- Model 5: Macroeconomic - UNEMP & CORPSPR; Idiosyncratic - none.
- Model 6: Macroeconomic - UNEMP & CORPSPR; Idiosyncratic - TAAA.
- Model 7: Macroeconomic - BBBCY & VIX; Idiosyncratic - none.
- Model 8: Macroeconomic - BBBCY & VIX; Idiosyncratic - TAAA & OROTA.
- Model 9: Macroeconomic - BBBCY & CORPSPR; Idiosyncratic - none.
- Model 10: Macroeconomic - BBBCY & CORPSPR; UNEMP & VIX; Idiosyncratic - TAAA & CDLGR.
- Model 11: Macroeconomic - BBBCY, UNEMP & CREFI; Idiosyncratic - none.
- Model 12: Macroeconomic - BBBCY, UNEMP & CORPSPR; Idiosyncratic - CDLGR.
- Model 13: Macroeconomic - BBBCY, UNEMP & CORPSPR; Idiosyncratic - TAAA.
- Model 14: Macroeconomic - BBBCY, UNEMP & CORPSPR; Idiosyncratic - none.

As described in Table 2 of the paper, all of the candidate models satisfy our basic requirements of model fit and intuitive sensitivities. Model fit, as measured by Adjusted R Squared (“AR2”), ranges from 87% to 97% across models, which is good performance by industry standard and broadly comparable.

The model performance metrics of the 14 models are presented in Table 3 of the paper, where these statistics are tabulated for the development sample 4Q01-4Q15, and out-of-sample 1Q16-4Q17, and the latter is evaluated under the three scenario generation models (Fed, VAR and MS-VAR) as well as perfect foresight (i.e., assuming we anticipated the actual paths of the macroeconomic and idiosyncratic variables). The author considers the following industry standard model performance metrics:

- Generalized Cross-Validation (“GCV”)
- Squared Correlation (“SC”)
- Root Mean Squared Error (“RMSE”)
- Cumulative Percent Error (“CPE”)
- Akaike Information Criterion (“AIC”)

It is observed from Table 3 of the paper that there is a great diversity of out-of-sample model performance across econometric specifications as well as across models for baseline economic forecasts, both in absolute terms and in comparison to the perfect foresight benchmark. It is further noted that in summary, out-of-sample performance across models is not assessed as being favorable by industry standards, even in the perfect foresight scenario. Measures of model (GCV, SC, RMSE & AIC) fit tend to be poor, and there is chronic underprediction of NCORs according to the CPE metric. While this is not conclusive, if it is assumed that we are near the end of an economic expansion, these results imply that most banks’ models will under-provision as we enter a downturn, which is evidence that the CECL standard may fail to address the problem of procyclicality that was the intent of the new accounting guidance.

Among the loss model specifications, he finds that generally the loss prediction specifications having a lower parameterization, as well as the MS-VAR scenario generation model, tends to produce better measures of model fit and a lower degree of under-prediction. Furthermore, relative to the perfect foresight benchmark, the MS-VAR model produces a lower level of variation in the model performance statistics across loss predictive model specifications.

Empirical implementation of the model risk quantification results are summarized in Table 4 of the paper, where the author tabulates the mean CECL loss under the model, the same in the worst case using the principle of relative entropy, and the relative model risk error (“RMRE”) measure. Table 4 shows that across credit loss and macroeconomic scenario generation models, the average RMRE is substantial. Considering scenario generation frameworks, it is observed that the MS-VAR model has a consistently lower RMRE measure as compared to the Fed or VAR models. Another pattern that the author observes is that, in the majority of cases, credit loss models having either more macroeconomic, or including idiosyncratic, factors in addition to a set of macroeconomic factors, both have higher model risk measures.