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RISK PERSPECTIVES

THE CONVERGENCE OF RISK, FINANCE, AND ACCOUNTING: CECL

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FROM THE EDITOR

Welcome to the eighth edition of *Risk Perspectives™*, a Moody's Analytics publication created by risk professionals for risk professionals.

This edition continues the theme started in the previous one – convergence of risk, finance, and accounting disciplines. After much delay and re-deliberation, the Financial Accounting Standards Board issued its new impairment standard, *Financial Instruments – Credit Losses,* commonly known as the current expected credit loss (CECL) approach. Since it is hailed as the biggest change in bank accounting, we would be remiss if we did not devote an edition to the US version of the IFRS 9 impairment standard.

With staggered implementation of the standard beginning in 2019, one may be inclined to postpone planning. That kind of thinking may prove to be a costly mistake. As Confucius said, "Real knowledge is to know the extent of one's ignorance." By most estimates, the new standard will result in an increase in overall allowance balances and may cause increased volatility in period-to-period provisions. Implementation of the new regulation will test practitioners and regulators as the financial industry seeks to understand the full effect of the changes. Impact assessments vary widely and the industry is only beginning to understand the questions that need to be answered. What are the appropriate approaches for each portfolio segment and what is the right level of segmentation, given a firm's complexity and size? What are the data gaps and how can we address them? What is the appropriate length of a reasonable and supportable forecast and how does this impact potential volatility of provisions?

Furthermore, incorporation of forecast information in what was previously a backward-looking process presents challenges for auditors and risk managers alike. Additionally, like any process that affects financial statements, the new allowance calculation is subject to strict internal governance and controls. For these reasons, parallel runs of six to 12 months in length will be critical. As one banker observed, there are no "mulligans."

One thing is clear: CECL compliance will be an interdisciplinary challenge. Implementation of the new impairment standard will require cross-functional working groups with representation from risk, accounting, treasury, finance, technology, and front-line business. Proactive firms will use the opportunity to revisit their data management and analytical platforms, looking for still-elusive "straight-through" processing analytics, workflows, and overlay management.

With this in mind, our first section throws the spotlight on the new standard from a range of perspectives. Mike McDonald and Seung Lee review the current state and near-terms plans in the CECL industry survey. Emil Lopez discusses similarities and differences between CECL and IFRS 9 impairment. Daniel Brown and Craig Peters remind readers of the stringent requirements on model risk management for CECL models. Cristian deRitis and Deniz Tudor look at industry-wide implications of the new standard. David Kurnov and Vainius Glinskis look at the impact of the impairment standard on structured security portfolios – something that often gets lost when firms focus on loan book impact first. We also review intersections of the new impairment standard and Basel capital rules in the article written by Julien Temim, and Shirish Chinchalkar looks at a bottom-up approach to modeling retail mortgages.

In Principles and Practices, Nancy Michael, Avinash Arun, and Helene Page discuss small business lending in a follow-up to their spring edition article. Samuel Malone and Ed Young discuss an approach to gauge counterparty credit risk in preparation for single-counterparty credit risk regulation. Brian Poi and Anthony Hughes propose a different use case for peer industry data in strategic planning and stress testing. In Innovation Zone, Joy Hart and Nihil Patel propose a new approach to strategic capital analysis. And finally, in Regulatory Review, we look at potential changes to Basel III with the much-publicized push toward standardized approaches in two articles by Richard Peterson and Jonathan Séror.

We hope you enjoy the edition, and as always, please stay in touch.

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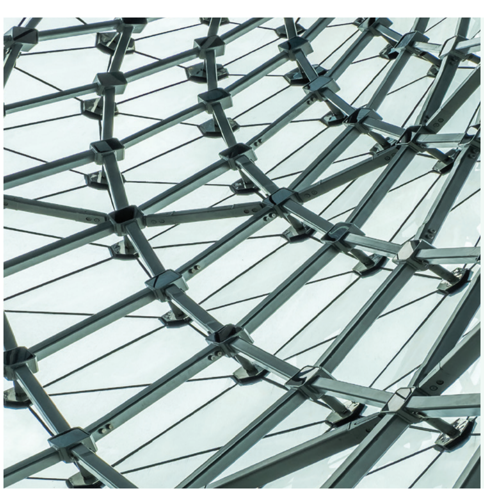

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SPOTLIGHT: CECL

NEW IMPAIRMENT MODEL: GOVERNANCE CONSIDERATIONS

By Daniel Brown and Dr. Craig Peters

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Although full CECL implementation is several years away, banks must begin preparing now to meet the impending requirements. In this article, we review some of the most important model governance considerations, including how to approach new modeling needs, key differences between models for CECL and models for AIRB and DFAST, and the differing expectations for less complex banks.

As US banks prepare for new financial instrument impairment standard implementation of the current expected credit loss (CECL) model, governance in general and model governance in particular will take center stage. Because CECL will have a direct impact on current period financial statements, banks especially will need to ensure the impairment processes and models used in allowance calculations are appropriate for that purpose. Banks should give serious consideration to model governance standards in the Federal Reserve's SR 11-7 supervisory letter and ensure that any models built for Basel advanced internal ratings-based (AIRB) or stress testing frameworks are not merely recycled for CECL estimates. Without appropriate challenge, validation, documentation, and auditing specific to the purposes of CECL, banks may not be able to demonstrate the appropriateness of the models for the new purpose.

CECL Governance Now?

It is still very early in the CECL implementation process, with a principle-based standard from the Financial Accounting Standards Board (FASB) issued and compliance deadlines three to four years out. Is it too early to raise the topic of model governance?

Various organizations have already raised the topic of governance related to IFRS 9. The Global Public Policy Committee issued a paper on IFRS 9 in June 2016, opening the document with a significant section on governance and controls. We agree that banks should consider the models, governance policies, and processes that will be needed so they can plan both the model development and approval frameworks for CECL.

But Do There Need to Be Models?

For some firms, especially for small non-complex banks, the current allowance for loan and lease losses (ALLL) process may be simple and highly judgmental. Since the FASB and regulatory agencies have already indicated that there will be flexibility on the required sophistication of the models, depending on the size and complexity of the bank and portfolio, it could be argued that those banks could use non-modeled approaches to set the ALLL reserve.

We believe that all approaches to estimating expected credit losses – even simple spreadsheet approaches – will likely be considered models. The existing model governance guidance from the Federal Reserve and Office of the Comptroller of the Currency (OCC), as laid out in SR 11-7 and OCC Bulletin 2011-12, provides a good perspective on how banks should approach the governance that will be required for any CECL estimates.

Consider the following aspects of CECL in the context of SR 11-7 guidance:

- **Forward-looking CECL estimates:** Technically, a forward-looking aspect is not part of the definition of a model. However, at the heart of the definition is a quantitative estimate of an uncertain quantity, and a forward-looking risk measure such as expected credit losses is by its very nature a quantitative estimate of an uncertain quantity.
- **Assumptions, data, and statistical and mathematical methods:** Even simple historical averages of losses rely on assumptions and data. The assumption that future losses will be reasonably similar to the historical loss rate is key to this approach. Moving to the life-of-loan approach required for CECL will require stretching the assumptions around historical loss rates, or applying more rigorous statistical and mathematical techniques. All of these elements are covered under SR 11-7, and banks at the very least will need to demonstrate their assumptions and methods are appropriate for CECL estimation.
- **Materiality:** CECL will affect current period financial statements, especially the income statement, but also the balance sheet through ALLL and the knock-on effect on retained earnings. Technically, materiality is also not part of the SR 11-7 definition of a model. But as a practical matter, models with important and significant uses are best treated as separate models on the inventory, so that appropriate model risk management isn't impeded by an effort to accommodate a condensed inventory.
- **Appropriateness of parameter quantification:** Any parameter quantifications used in CECL estimation have to be appropriate for the portfolio or individual loan in question. Even simpler methodologies using historical charge-off rates or expected loss (EL) rates should be appropriate to the life of loan loss estimation. More sophisticated methods employing probability of default (PD), loss given default (LGD), or exposure at default (EAD) will likewise need to be appropriate for CECL estimation.

Another practical reason to have a separate model on the inventory is that all models under SR 11-7 require ongoing monitoring. Monitoring PD, LGD, and EAD separately, devoid of the connection as factors for use in CECL allowances, wouldn't be appropriate.

CECL Governance for Banks Subject to AIRB and DFAST

Even Basel AIRB and stress testing banks will likely need to generate "new" models from a governance perspective. Although the AIRB and stress testing requirements overlap significantly with CECL requirements – all of them require an estimate of expected credit losses of some sort – the differences between the three directives mean that governance of the models will need to be tailored to the goals of the effort.

Banks will need to ensure that CECL models are appropriate for their intended purpose, so it is likely that banks cannot reuse AIRB or stress testing models as they are. Basel or stress testing models may provide foundational elements for CECL, but there are material differences between CECL, the Basel EL calculation, the stress testing credit losses, and provision projections. The key differences include:

- **Credit loss horizons:** Basel AIRB considers a one-year horizon, and stress testing considers a 13-quarter projection horizon. CECL will require banks to estimate an expected impairment value over the life of the loan. Banks will need to consider the assumptions that go into all the component CECL models and ensure that they are appropriate to the life-of-loan calculation.
- **Parameters (PD/LGD/EAD):** Basel AIRB requires through-the-cycle (TTC) PDs and downturn LGDs and credit conversion factors (CCF). Stress testing expects point-in-time (PIT) or scenario-specific parameter values. CECL is closer to stress testing in that all parameter values should match the scenarios used, but banks should be wary of assuming stress testing parameters are appropriate for CECL. In particular, CECL requires a "life of loan" estimate of losses, and the parameter treatment will be particular to the context of each portfolio, or perhaps even each loan. In

some cases, CECL may require PD and LGD curves to match loan cash flows over the life of the loan.

» **Scenarios:** IFRS 9 requires banks to generate ECL estimates with consideration of current and potential future conditions. While there is not an explicit requirement for a scenario-based approach, it is likely that many banks will utilize their existing stress testing scenario framework in the CECL context. But we caution: The Comprehensive Capital Analysis and Review (CCAR) and Dodd-Frank Act Stress Test (DFAST) baseline scenarios (regulatory or internal) may not be appropriate or adequate for life-of-loan forecasting.

» **Conservatism**: In both the Basel and stress testing frameworks, model deficiencies or limitations can be addressed by "topping up" the credit loss estimates, such as through management adjustments. With CECL, because the goal is to get to an expected impairment estimate, one-way adjustments (upward) may not be appropriate. With ALLL generally, the goal is to have the right amount of reserves (and quarterly provisions) rather than a generous buffer. In the current reserving framework, banks must justify their provision and reserves and ensure that they are not manipulating earnings. As guidance develops around CECL, it will become clearer what regulators will expect in terms of adjustments for modeling deficiencies. But at this point, banks should not assume that the conservative management adjustments for AIRB and stress testing can be applied in CECL.

Generally, AIRB and stress testing banks will need to look at all aspects of CECL modeling separate from their existing frameworks. While many components of those frameworks may be appropriate in CECL, banks should check all assumptions for appropriateness in the new CECL context.

CECL Governance for Less Complex Firms

Less complex banks – those using the Basel standardized approach and below the DFAST threshold – will likely be able to use less complex approaches for CECL estimation. But SR 11-7 already recognizes that scale and complexity impact appropriate modeling approaches of risk estimation. For banks that are starting without AIRB or stress testing frameworks, the governance will require that they ask the same basic question: Are the assumptions, data, models (even spreadsheets), and overall process appropriate to the estimation of expected lifetime impairment of loans and leases?

While these banks may not have experience in setting up the required governance elements, they should be able to draw on existing industry experience from the earlier Basel and stress testing efforts and modify what other (larger, more complex) banks have done to meet their own needs for CECL.

Basic Considerations for CECL Governance

Given the materiality of CECL numbers and the impact on a bank's financial reporting, we expect that banks will need to develop governance programs that address the following aspects:

» Appropriateness of data, methods, and models for CECL purposes

» Reconciliation of portfolio positions

» Benchmarking of CECL estimates against Basel and/or stress testing results

» Sensitivity of models to assumptions and limitations, with adjustments appropriate for an expected measure of credit losses (not just adding a cushion for conservatism)

» Understanding of models by senior management and the board of directors

» Internal processes for challenge, validation, review, approval, backtesting, and outcomes analysis

» Tracking of results from quarter to quarter, to understand movements in outcomes and whether they conform to expectations (i.e., sensitivity of models)

Conclusion

For the CECL process and all of the modeling elements associated with it, AIRB and stress testing banks will need to take a fresh look at the methods, avoiding the assumption that models that were good enough for other purposes will meet the needs of CECL. And less complex banks that are building completely new frameworks will need to address these elements as well, even for the simpler approaches.

Banks should recognize in advance the importance of two items:

- **Documentation:** Key documentation needs to include model development, validation, model use and maintenance, and ongoing monitoring.
- **Policies:** Existing policies for Basel or stress testing should be modified to meet CECL's specific needs. Given the primary role of the finance function (and the chief financial officer) in banks' ALLL calculations, policies will need to address the enterprise-wide nature of the CECL effort and clearly define authority, approval, and decision-making powers. Banks should consider what will be needed for both internal and external auditors to provide their opinion statements with regard to CECL estimates.

Board of Governors of the Federal Reserve System. "SR 11-7: Guidance on Model Risk Management." April 4, 2011.

Global Public Policy Committee. "The implementation of IFRS 9 impairment requirements by banks." June 17, 2016.

Office of the Comptroller of the Currency. "OCC Bulletin 2011-12: Sound Practices for Model Risk Management." April 4, 2011.

CECL'S IMPLICATIONS FOR BANK PROFITABILITY, SYSTEM STABILITY, AND ECONOMIC GROWTH

By Dr. Cristian deRitis and Dr. Deniz K. Tudor

In this article, we analyze the potential effects of upcoming CECL regulations on lenders and explore the impact of CECL under different Moody's Analytics scenarios. A poorly timed transition could lead to a market-wide liquidity shortage or a crisis in economic activity. We provide suggestions on how the transition to CECL can be managed smoothly for minimal economic impact.

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The switch in accounting rules to a current expected credit loss (CECL) framework is intended to increase stability in the financial system and improve liquidity throughout the economic cycle. Under the new framework, firms will begin reserving for potential losses when they first book loans rather than setting aside reserves only after loan performance deteriorates.

However, as with most changes in rules and regulations, what looks reasonable and appropriate in theory may not turn out as such in practice. At a minimum, CECL will lead to front-loading losses relative to the current system. Transitioning from the current system to this new approach may inject some volatility into bank earnings and profitability. CECL also introduces uncertainty into accounting calculations, as economic forecasts are imperfect over long horizons.

In this article, we consider the adoption of CECL with an eye toward assessing its potential benefits – and risks – to the financial system and the broader economy.

Procyclicality Gone Wild

Current accounting rules utilize a "probable and incurred loss" standard which requires lenders to reserve an allowance for loan and lease losses (ALLL) by applying recent performance trends to their outstanding books of business. So, if 10% of loans with certain characteristics have defaulted in the recent past with no recoveries, then lenders should assume the same going forward and add 10% of outstanding balances to their loss reserves. The benefit of this approach is that it is relatively simple to implement and is seemingly objective, as it does not permit the lender to make any rosy assumptions about future performance that would cause it to under-reserve.

But this assessment is not quite correct. Simplicity can come at the cost of accuracy. Lenders need to categorize or cohort their portfolios in order to calculate the historical loss rates to be applied to their current books of business. Just as politicians can influence election outcomes by creatively defining voting districts (i.e., gerrymandering), lenders' discretion in determining the cohorts or segments of their portfolios could have an impact on computed loss rates. Auditors and regulators may review and challenge lender processes, but some risk remains.

In addition, lenders could influence reported outcomes through the determination of an appropriate loss emergence period. Typically, consumer loans do not default instantaneously. Many borrowers who miss a loan payment are able to catch up and cure before transitioning to a deeper state of delinquency or default.

Under current accounting rules, lenders need to account for this process when assessing the likelihood and severity of losses in their current portfolios. Based on the performance history of

Such behavior can exacerbate the recession as lenders are forced to pull back from supplying credit at precisely the time that borrowers and the economy may need credit the most.

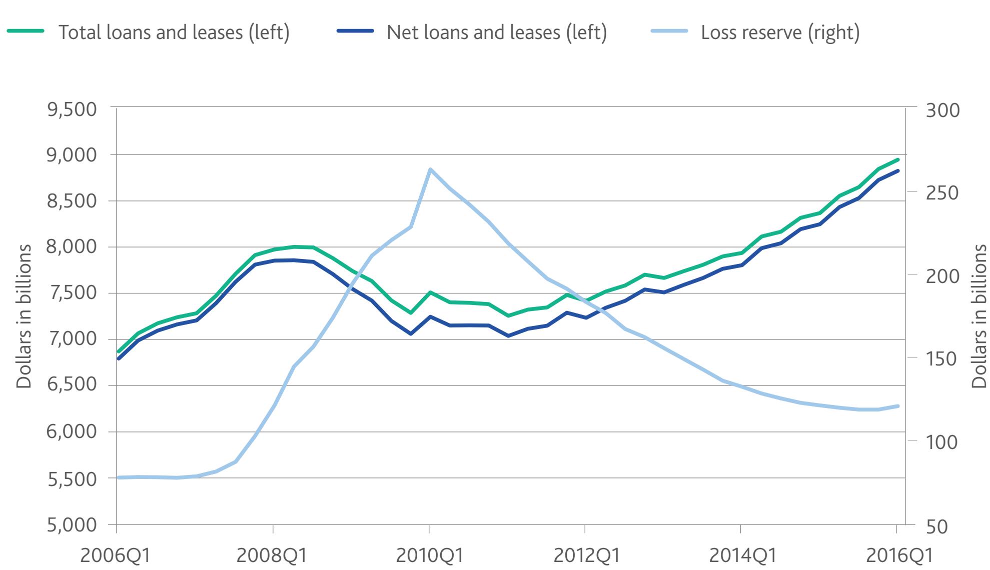
> Perhaps the biggest criticism of the current process is that it is backward-looking. By restricting default analysis to recent history, loss reserves can become highly procyclical.

their own portfolios, they may determine the average number of months it takes for loans within a given book of business to experience losses. They then look back over recent history for a similar number of months to make their historical loss calculations. Again, while the determination of the emergence period may be largely objective, some discretion in analytical choices can influence results.

Lenders also end up over-reserving toward the end of recessions, when realized losses fall as the economy improves. The capital release that follows introduces volatility into the system as lenders flush with capital scramble to deploy it wherever possible, leading to loosened standards and the heightened potential for mal-investment and bubble formation.

This procyclicality was evident during the Great

Figure 1 Total loss reserves at FDIC-insured institutions

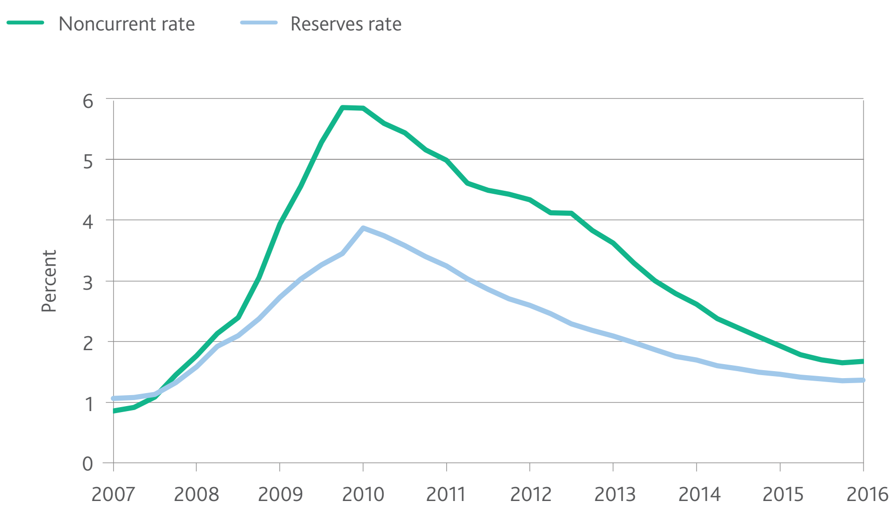


Sources: FDIC Quarterly Banking Profiles, Moody's Analytics

Perhaps the biggest criticism of the current process is that it is backward-looking. By restricting the analysis to recent history, loss reserves can become highly procyclical, as shown in Figure 1. Leading up to a recession, loss reserves are low and firms must rapidly add to their ALLL as delinquencies and defaults soar.

Recession and was one of the motivations behind the adoption of the CECL standard. In fact, CECL was initiated by the Financial Crisis Advisory Group (FCAG) and is widely supported by US banking regulators. Figure 2 shows that the increase in the reserve rate in commercial banks lagged the increase of noncurrent loans

Figure 2 Reserve and noncurrent rates for loans and leases at commercial banks



Sources: FDIC Quarterly Business Report, Moody's Analytics

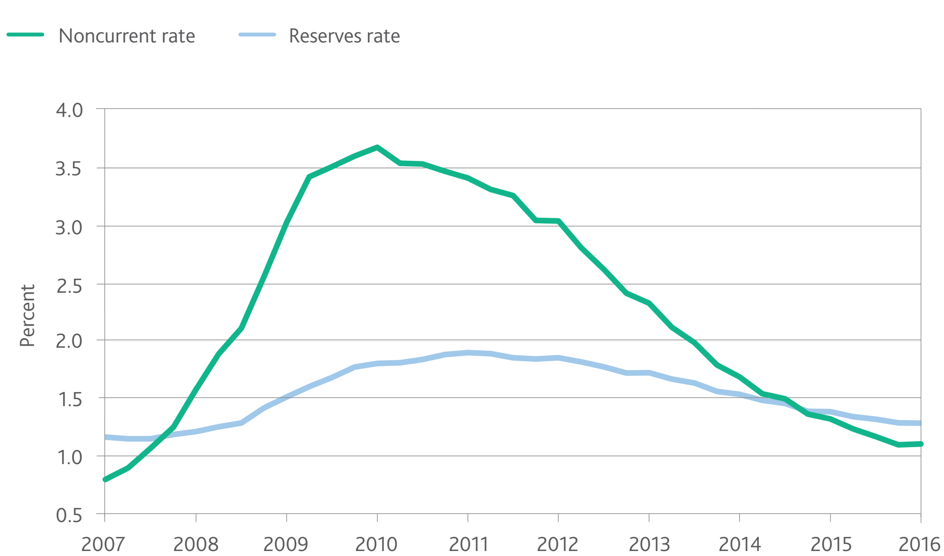
by several quarters in 2009. Furthermore, the reserve rate declined more slowly than the noncurrent rate in 2012.

The divergence between reserve rate and noncurrent rate was even larger for community banks, as shown in Figure 3, although this is largely a function of the higher credit quality of loans at these institutions; note the difference in scale on the y-axes of Figures 2 and 3. The community bank experience is closer to the ideal envisioned under CECL, where reserves are sufficiently high at loan origination and require only small additions when the economy moves into recession.

CECL to the Rescue

Recognizing the flaws in incurred loss accounting, the Financial Accounting Standards Board (FASB) proposed CECL, which requires firms to estimate lifetime expected loan losses starting from the date of inception. In this

Figure 3 Reserve and noncurrent rates for loans and leases at community banks



Sources: FDIC, Moody's Analytics

approach, loss projections are less dependent on recent history and there is less room for individual discretion regarding segmentation and emergence periods.

However, the new approach is not without its own challenges and potential pitfalls. Many firms may have insufficient data with which to estimate lifetime losses, thereby requiring some supplementation with external sources. Figure 4 provides a list of information necessary to successfully conduct CECL calculations. Even large lenders – which have already gone through Dodd-Frank Act Stress Tests (DFAST) and Comprehensive Capital Analysis and Review (CCAR) regulations and hence are familiar with the types of models needed for CECL – may wish to take advantage of large, industry-level datasets in order to more easily justify the objectivity of their processes.

Given that CECL introduces an element of forecasting to the loss reserving process, auditors and regulators may be justifiably concerned that firms could assume an economic outlook that projects a more favorable – but less realistic – outcome in order to minimize the amount of money they need to set aside. While specific guidance from auditors or regulators has not been issued, we believe that one of two approaches for determining economic scenarios will be acceptable.

Figure 4 Data necessary for CECL compliance

What kind of data will firms need for CECL?	
Origination information	» Date (vintage) » Maturity/term of installment loans » Credit score » Loan-to-value (LTV) ratio » Fixed or variable rate » Geography
Other loan information	» Troubled debt restructuring (TDR) loans and dates » Renewal » Modification » Current credit score » Current LTV
Loss given default (LGD) information	» Current collateral values » Workout/recovery
For revolving loans or lines of credit	» Credit limits » Draws » Utilization rates » Exposure at default (EAD)
Ongoing changes to credit risk status	» Delinquencies » Defaults » Prepayments » Payoffs » Credit ratings/grades
Other portfolio information	» Purchased loans
Economic data	» Home prices » Unemployment rates
Length of data	» Minimum of an economic cycle
Frequency of data	» Quarterly or monthly

Source: Moody's Analytics

Under the first approach, lenders would estimate losses on their loans under multiple scenarios: one upside, one downside, and one baseline scenario. In this case, the reported losses under CECL would be derived as a probability-weighted average of the likelihood of each scenario – rather than relying solely on a single econometric model for scenarios.

Alternatively, firms and auditors may wish to adopt a consensus-based approach when determining the economic scenario to use for CECL. That is, they may prefer to average the baseline economic projections of multiple government and professional economic forecasters to create a single consensus scenario of the most likely path for future economic activity and growth. Lenders would then use this scenario to generate their CECL loss numbers with no additional weighting required.

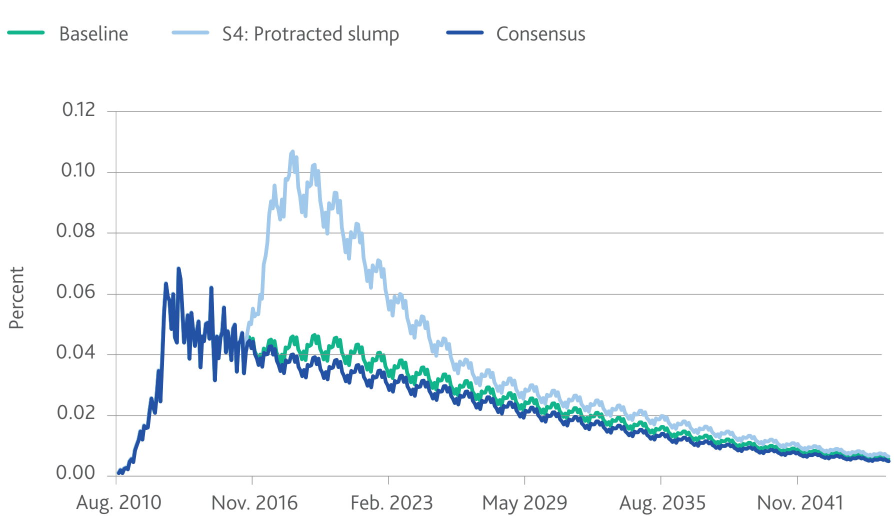
Modeling Options for CECL

As lenders begin to consider the impact of CECL on their accounting processes, they will also consider which models are most appropriate for their situations. A variety of approaches are available, ranging from roll-rate and vintage-cohort models to more sophisticated expected loss and regression models. Lenders that have been through the Federal Reserve's DFAST or CCAR stress testing process may be tempted to reuse their models for the CECL exercise. Recycling or adapting existing models for CECL would be cost-effective, but there may be some concern that models developed for stress testing may be overly conservative for financial accounting purposes.

CECL models share many of the same characteristics as stress testing models. That is, models for both objectives should account for the life cycle of loans, origination vintage effects, time varying effects, seasonality, and a variety of borrower and loan characteristics. Depending on the particular model specifications, most models developed for stress testing could potentially be used for CECL calculations with few modifications. See Figure 5 for an example of dollar loss rates projected 30 years out for a bank portfolio.

While larger lenders may develop their own internal models for CECL, smaller lenders may be unable to do so, given a lack of historical performance data. Formal development of models including backtesting, sensitivity analysis, documentation, and validation may also prove cost-prohibitive to some lenders. The

Figure 5 Projected dollar loss rates



Sources: Equifax, Moody's CreditCycle™

availability of cohort-level models estimated on industry-wide consumer credit data allows lenders to easily obtain current expected credit loss estimates across all consumer credit products by vintage-cohorts. This permits lenders to generate forecasts by simply merging or looking up projected losses by loan category – even for purchased portfolios for which they have limited performance information. Because industry models have been developed and validated on the entire universe of data, lenders can obtain robust estimates for specific loans on their books.

Lenders can also use industry models to produce credit loss estimates of future loan originations to estimate and prepare for CECL's impact on new loan bookings. Although lenders are strongly encouraged to start preparing for CECL by performing gap and impact analyses, lenders must maintain allowances for incurred loans and leases in compliance with current generally accepted accounting principles (GAAP) until CECL is officially adopted. As a result, prudent lenders will likely increase retained earnings in anticipation of CECL. This will make their Tier 1 capital ratios look impressive in the short-term (to the delight of regulators) while limiting dividend payments and share buy-backs (to the dismay of shareholders).

Timing is Everything

Given our assessment of the current and future states of the loss reserving process, we believe the adoption of the CECL framework is a positive step, both in terms of providing investors with a more accurate assessment of the financial positions of lenders, and in terms of improving the stability of the overall financial system. Firms must adopt the CECL framework by 2019 or 2020, depending on firm size, which allows sufficient time to change internal systems.

But in our opinion, they cannot start the transition soon enough. As described in the previous section, there are multiple moving parts in the process that will require significant time to develop, test, and deploy, especially if a lender has not been through the CCAR/DFAST stress testing processes yet. Given that most lenders will need to increase their loss reserves once CECL takes effect, it would be prudent to run both the current and the new accounting standards in parallel so lenders have ample time to transition.

> Adoption of the CECL framework is a positive step, both in terms of providing investors with a more accurate assessment of the financial positions of lenders, and in terms of improving the stability of the overall financial system.

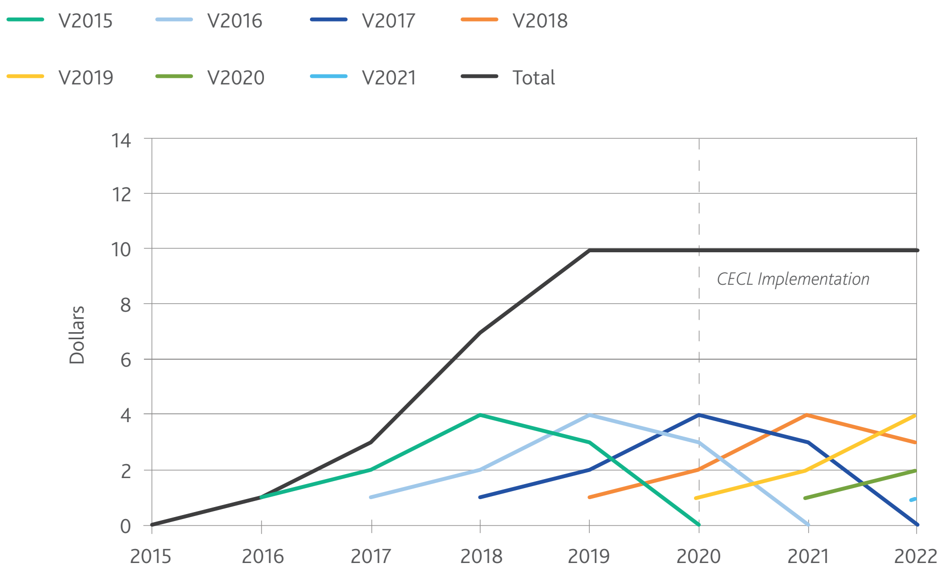
Figures 6 and 7 give a simple example of such an analysis, comparing the current ALLL incurred loss approach to CECL using the following simplifying assumptions:

1. Assume five-year installment loans with each vintage originating with a $100 balance.
2. Assume each vintage follows the same pattern of losses over five years (i.e., 10% cumulative loss rate with $1 of loss in the first year, $2 of loss in the second year, $4 of loss in the third year, $3 of loss in the fourth year, and $0 of loss in the fifth year).
3. Assume perfect foresight in reserving so that each year the lender can perfectly anticipate losses in the following year.
4. Assume CECL takes effect in 2020.
5. Assume 0% discount rate for the sake of simplicity.

This simple example illustrates the potentially substantial effect of CECL, as all future losses on existing loans will need to be reserved instantaneously in 2020. In reality, the impact of CECL for each lender will depend on several factors, including:

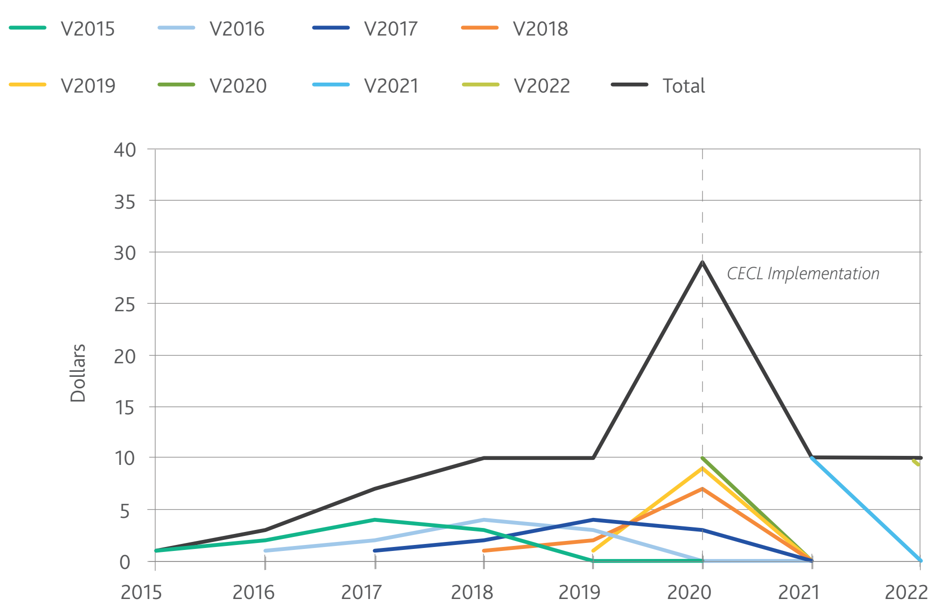
- Age and expected remaining life of the loans in a portfolio. For example, the larger the number of new originations at the time of transition, the bigger the impact.

Figure 6 Example of reserve contributions by origination vintage under the incurred loss approach



Source: Moody's Analytics

Figure 7 Example of reserve contributions by origination vintage under the CECL approach



Source: Moody's Analytics

- Portfolio quality, defined by origination credit score, loan-to-value ratio, debt-to-income ratio, etc. The impact will be lower on higher-quality portfolios.
- Types of loans in portfolio. Installment versus revolving as future draws could impact loss reserves.
- Terms of loans. For example, longer-term loans could lead to higher loss reserves under the life-of-loan assumption.
- Geographic location of loans. Geography will affect the quality of the portfolio. Exposures in stressed areas could have higher loss projections.

- Current status of loans. Loans that are currently delinquent will have higher loss projections than non-delinquent loans.

Finally, the impact of CECL will depend on the economic conditions at the time of loan origination as well as every subsequent reporting period.

investors will have an understanding that lender profitability will be less volatile in the future.

If lenders wait, however, and rush to increase reserves closer to the deadline, it could significantly impact profitability. In a worst-case scenario, the rush could lead to a liquidity crisis as firms hoard funds and drive up the cost of capital in a mad dash to comply with regulations. Such a financial shock would be felt immediately in the real economy as banks reduce lending to both the commercial and household sectors. Economic activity would slow as a result of a credit crunch.

> Firms may need to increase their ALLL by as much as 30% to 50% over current levels. If lenders plan for this eventuality over the next three to four years, the overall impact to both earnings and the economy should be minimal.

From an economic perspective, the timing of the transition will be critical. CECL front-loads losses, as compared with the current system. As an immediate result, firms will need to significantly increase overall loss reserves from current levels. According to an analysis performed by the Office of the Comptroller of the Currency (OCC), firms may need to increase their ALLL by as much as 30% to 50% over current levels.[1] If lenders plan for this eventuality over the next three to four years, the overall impact to both earnings and the economy should be minimal. Firms may retain more of their earnings and report lower profits than they might have previously, but

Figure 8 provides some sensitivity analysis around the potential increase in reserve allowances by assuming various impact levels of CECL. We compare reserve amounts from the start of the Great Recession (2007Q4) with those realized at the middle of the recession (2008Q3) and at the end of the recession (2009Q2). We also report the realized allowance for 2010Q2 when reserves hit a historical

Figure 8 Potential increase in reserve allowances for all FDIC-insured institutions, assuming various impact levels of CECL

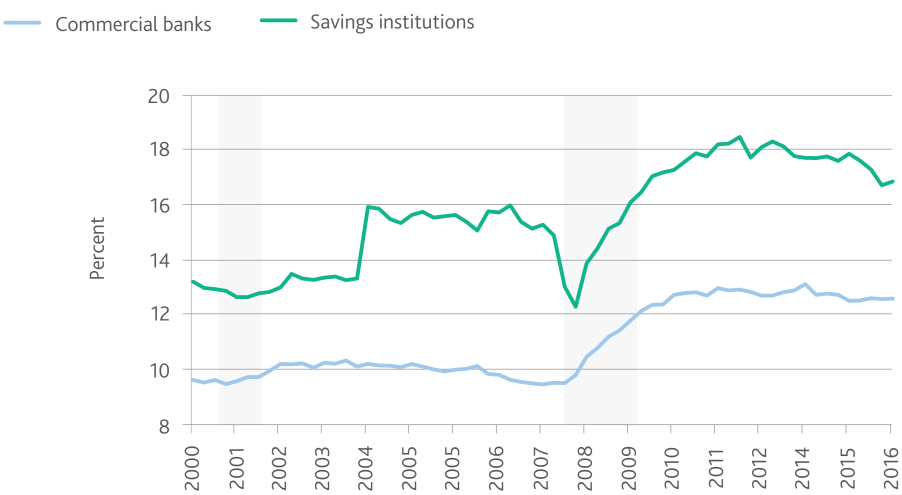
(dollar figures in millions)		Potential Percentage Increase Due to CECL					
	Historical Value	5%	10%	20%	30%	40%	50%
2016Q1 reserves for losses (current)	$120,663	$6,033	$12,066	$24,133	$36,199	$48,265	$60,332
2007Q4 reserves for losses (start of recession)	$102,552	$5,128	$10,255	$20,510	$30,766	$41,021	$51,276
2008Q3 reserves for losses (mid-recession)	$156,445	$7,822	$15,645	$31,289	$46,934	$62,578	$78,223
2009Q2 reserves for losses (end of recession)	$211,157	$10,558	$21,116	$42,231	$63,347	$84,463	$105,579
2010Q2 reserves for losses (historical max since 2006Q1)	$251,559	$12,578	$25,156	$50,312	$75,468	$100,624	$125,780

Sources: FDIC, Moody's Analytics

1 Curry, Thomas J. "Remarks by Thomas J. Curry, Comptroller of the Currency, Before the AICPA Banking Conference, Washington, D.C." September 16, 2013.

maximum. Finally, total outstanding reserves as of 2016Q1 were reported to be around $120 billion. Therefore, if CECL went into effect today and the impact was 30%, then FDIC-insured institutions would need to increase their could be exacerbated if lenders held back new originations to reduce the impact of CECL, as new originations will impact reserves the most. The effect could be increased further if banks have insufficient capital to meet

Figure 9 Total risk-based capital ratios



Sources: FDIC Quarterly Banking Profile

reserves by about $36 billion based on today's numbers.

Economic conditions could change by the time CECL takes effect, so we also consider what the reserves could be at a date closer to CECL's 2020 implementation, given potential changes in the economic environment.

In order to estimate an upper bound on CECL's impact, suppose that lending standards loosen over the next few years and the economy experiences another Great Recession starting in 2019, just as CECL is scheduled to take effect. Also assume that banks need $251.6 billion in reserves, as they did during the Great Recession, and that the transition to CECL will require a 30% immediate increase in reserves. Banks would need to add another $75.5 billion to their reserve amount.

In other words, a total of $327.1 billion would need to be dedicated to reserves and would therefore be unavailable for lending to consumers. A potential credit crunch as such their reserve obligations. This could force the Federal Reserve to intervene and either increase discount window borrowing or lend directly to institutions – as occurred during the last recession.

Allaying some of the concerns around the adoption of CECL is the fact that the US banking system is well-capitalized. According to the FDIC, both commercial banks and savings institutions increased their levels of capital while simultaneously reducing the number of nonperforming loans in their portfolios in the wake of the Great Recession. Capital ratios have increased to record high levels as a result, far exceeding the 8% ratio that defines well-capitalized institutions according to the Federal Reserve's Regulatory Capital Guidelines [2] (see Figure 9). Utilizing some of this capital to meet CECL obligations would still leave the banking system as a whole adequately capitalized, although some individual institutions would undoubtedly be strained.

2 Federal Reserve System. "Federal Register, Vol. 78, No. 198." October 11, 2013.

While the Moody's Analytics baseline economic forecast suggests a much more modest scenario than a severe downturn, such an outcome is not without precedent given the Great Recession. The opaqueness of credit market derivatives, combined with strict market-to-market accounting rules, exacerbated the financial stress caused by the collapse of Lehman Brothers across the financial system. A recession may have been inevitable, considering imbalances introduced by over-investment in the housing sector. But additional flexibility and forbearance in the financial system may have prevented a garden-variety recession from turning into the Great Recession.

Moreover, the regulations brought on by DFAST caused further tightening in credit markets and are cited as one of the reasons the recovery this time around has been one of the slowest. Some of the consumer credit markets such as mortgage and bankcards have started to recover only recently and are seeing a slight loosening in standards. Another tightening in credit caused by another policy change – if not timed correctly – could precipitate an unforeseen chain of events.

The Future is Now

By acting as a countercyclical buffer, CECL holds great potential to improve the stability of banks and the overall financial system, but only if the transition is orderly. Lenders need to start preparing as soon as possible, and regulators need to be ready to adjust to conditions on the ground as the CECL deadline approaches. With the labor market steadily improving and consumer credit losses near record lows, the current environment is ideal for lenders to prepare for the transition. Should the implementation of CECL coincide with a stumble in economic performance, the benefits of transitioning will be muted at best and could trigger a recession at worst. For their own benefit, as well as the benefit of the financial system and the broader economy, all lenders should start preparing for CECL without delay.

MORTGAGE MODELS FOR CECL: A BOTTOM-UP APPROACH

By Dr. Shirish Chinchalkar

Dr. Shirish Chinchalkar
Managing Director, Quantitative Finance

Shirish heads the group responsible for building credit models for different retail asset classes such as US, UK, and Dutch residential mortgages, US auto loans, and credit cards, as well as for several different US and EMEA asset-backed securities. His group also implements the models in the Portfolio Analyzer platform which is used for stress testing and risk management of retail and structured portfolios. He has a PhD from Cornell University and a BTech from IIT Bombay.

In this article, we describe how a loan-level modeling approach can be used to forecast credit losses in residential mortgages. We review the challenges a bank may face in complying with the FASB's recent Accounting Standards Update on reporting credit losses. In particular, we show how historical, current, and forward-looking information can be used to estimate credit losses. We also address other modeling and implementation considerations as they pertain to the estimation of credit losses.

Introduction

When building and implementing econometric models for different asset classes, a modeler needs to carefully examine the requirements from the perspective of the end users of the models. A trader of whole loans may be more interested in the accurate modeling of loan-level cash flows and exploiting any statistical arbitrage. A servicer is likely to be concerned about delinquency transitions and time to liquidation. Regulatory stress testing requires that the models demonstrate sensitivity to macroeconomic conditions. Risk management requires that the models correctly capture the correlation between different assets in the portfolio.

The recently issued Accounting Standards Update (ASU) by the Financial Accounting Standards Board (FASB) introduces several considerations that banks must incorporate into their estimation of credit losses:

» The bank must use historical information, current information, and forward-looking information to arrive at the loss estimates.

» The losses must be estimated over the life of the loans.

» The effect of prepayments must be accounted for when calculating the losses.

A typical bank's whole loan retail portfolios consist of residential mortgages and home equity lines of credit (HELOCs), auto loans, credit cards, and other consumer loans. Banks usually have the largest exposure to residential mortgages and HELOCs. Although the number of mortgages is usually smaller, the balances on mortgages are also much larger than those on auto loans or credit cards. Moreover, residential mortgages and HELOCs can have several different products, such as fixed-rate and adjustable-rate mortgage (ARM) loans and loans with different terms and maturities. Therefore, as compared to other retail assets, mortgages tend to be less homogenous.

Retail portfolios can be analyzed using a top-down (segment-level) or bottom-up (loan-level) approach. This paper shows how we can use a loan-level modeling framework to arrive at the expected credit losses on residential mortgage portfolios.

A Loan-Level Framework

A loan-level or bottom-up approach involves constructing econometric models for each loan in the portfolio. Results can be aggregated over all the loans in different cohorts or segments to arrive at segment-level or portfolio-level results.

Loan-level models are usually hazard-rate models and can be constructed in a competing risk framework. The data is naturally organized as panel data; each loan has multiple observations through time. Defaults and prepayments compete with each other in a multi-period setting. Survival models in this framework can be built using a panel logit model.

A bottom-up approach has the advantage that the results are naturally available at the highest level of granularity. The explanatory variables, such as loan and borrower characteristics and macroeconomic variables, are used at the loan level. Likewise, the performance variables, such as defaults, prepayments, cash flows, and losses, are modeled at the loan level. Heterogeneity of the loan characteristics – for example, different mortgage products such as first or second lien loans, adjustable- or fixed-rate loans, low-LTV (loan-to-value) or high-LTV loans, or loans with different levels of credit risk – can be easily accommodated.

Building loan-level models requires reliable historical loan-level data. This can be onerous and expensive. If the loan-level data is not reliable, the models that are built may need to be recalibrated. The implementation can also require additional resources.

Next, we look at some of the considerations in the ASU and see how they can be addressed in this framework.

Portfolio Segmentation

A joint statement by the Federal Reserve, FDIC, National Credit Union Administration (NCUA), and Office of the Comptroller of the Currency (OCC) clarifies their position on segmentation of the portfolio. Although the standard allows for institutions to measure the expected credit risk on a collective or pool basis provided loans have similar risk characteristics, the statement says, "If a financial asset does not share risk characteristics with other financial assets, the new accounting standard requires expected credit losses to be measured on an individual asset basis."[1] In a loan-level modeling approach, this point is automatically addressed because each loan is treated separately. The migration of a loan from one risk bucket to another as a result of changes in the borrower's credit score can also be accommodated in loan-level models.

Use of Historical, Current, and Forward-Looking Information

The measurement of expected credit losses is to be based on relevant information about past events, including historical experience, current conditions, and reasonable and supportable forecasts that affect the collectability of the reported amount. Let us now see how these conditions are incorporated into a loan-level analysis.

Past events enter the models in a few different ways. First, terms in the models such as the spread at origination (SATO) – the difference between the interest rate on the mortgage and the prevailing market mortgage rate at loan origination – capture the credit riskiness of the borrower at loan origination. Second, factors such as the change in unemployment rate from loan origination or the change in home prices from loan origination reflect the macroeconomic conditions at loan origination. Third, the trajectory of interest rates and home prices from loan origination produces prepayment opportunities to the borrower. "Burnout," which captures the unwillingness or inability of the borrower to prepay, is another factor that captures historical macroeconomic information in the model.

The models themselves are estimated using the default, prepayment, and loss experience in the historical dataset used to build the model. Therefore, as long as the models are built using the reporting institution's data or are calibrated to it, the models can account for the historical experience.

Paragraph 326-20-55-3 in the ASU provides some commentary on the use of historical data:

Historical loss information generally provides a basis for an entity's assessment of expected credit losses. An entity may use historical periods that

1 FRB, FDIC, NCUA, and OCC joint statement, 2016.

represent management's expectations for future credit losses. An entity also may elect to use other historical loss periods, adjusted for current conditions, and other reasonable and supportable forecasts. When determining historical loss information in estimating expected credit losses, the information about historical credit loss data, after adjustments for current conditions and reasonable and supportable forecasts, should be applied to pools that are defined in a manner that is consistent with the pools for which the historical credit loss experience was observed.

Current conditions enter the models in a few different ways. First, the delinquency status of the mortgage directly affects the probability of prepayment and default on the mortgage. Second, the current outstanding balance is used to determine the updated LTV of the borrower, which is one of the dominant factors in default and loss given default (LGD) models.

When we build a loan-level econometric model, we naturally separate out and capture the effects of macroeconomic drivers and loan and borrower characteristics. This ensures that any increase or decrease in the historical loss over different periods has been accounted for through the use of the appropriate driver. Therefore, when the models are used in forecasting the credit losses, an exact match of the loan-level characteristics with the historical data is not necessary. What is necessary, though, is that the data used in building the models is a superset of the data on which the models are run.

Forward-looking information is incorporated through the use of macroeconomic forecasts. These contain future home prices, unemployment rates, and interest rates, which enter the models through different factors such as updated LTV, unemployment rate shocks, and interest rate spreads.

Estimating Credit Losses Over the Life of the Loan

Expected credit losses are to be calculated over the life of the loan. In this section, we will consider how this calculation can be performed using a discounted cash flow method. In a discounted cash flow method, the loan's cash flows, such as principal, interest, prepayments, and recoveries, should be estimated over the contractual life of the loan. Note that the expected life of the loan is much shorter than the contractual life. For example, a typical 30-year fixed rate mortgage may only have an average life of 10 years. When projecting cash flows in a competing risk framework, we apply the probabilities of prepayment and default in each period and determine the expected survival probability of the loan at the end of each period. Based on this survival probability, we can calculate the expected cash flows in each month from the reporting date. After discounting the cash flows by the effective interest rate, we arrive at the amount expected to be collected. Therefore, the calculation of the expected credit losses over the life of the loan does not pose any additional challenges as long as hazard-rate models are applied in a multi-period setting.

> As long as the models are built using the reporting institution's data or are calibrated to it, the models can account for the historical experience.

Estimating Losses for Loans with Low Credit Risk

Paragraph 326-20-30-10 states:

An entity's estimate of expected credit losses shall include a measure of the expected risk of credit loss even if that risk is remote, regardless of the method applied to estimate credit losses.

When we use a loan-level econometric model, the model is estimated over the universe of loans with different credit qualities. Therefore, although the historical loss on a small set of good loans may be zero, the models are likely to estimate a low but non-zero probability of default for a large set of similar loans. The actual loss estimate may or may not be zero, depending on the estimated value of the collateral at the time of default or liquidation.

Incorporating Prepayments in the Analysis

Mortgages have a built-in prepayment option whereby a borrower can choose to refinance a mortgage by borrowing from one financial institution at a lower rate and paying off the existing loan. Additionally, the borrower can pay off the mortgage by selling the house. Most mortgages do not have a prepayment penalty, so a borrower is free to exercise this option depending on the prevailing interest rates and other factors. In a competing risk framework, the conditional prepayment and default hazard rates are estimated. They compete with each other when implemented in a multi-period framework. If prepayments rise, then fewer loans are available to default. As a result, the cumulative or lifetime probability of default of the loans decreases.

When calculating the credit losses over the expected life of the loan, no special considerations are needed to determine the expected life. When performed over the contractual life of the loan, the probabilistic calculations naturally produce the expected life of the loan along with the option-adjusted expected credit losses of the loan. In other words, the effect of prepayments on the estimated life of the loan is accounted for in this modeling approach.

Use of Reasonable and Supportable Forecasts

The ASU mentions the use of reasonable and supportable forecasts in several places throughout the document. We have already seen that given a macroeconomic forecast, the calculation of the expected credit loss using a discounted cash flow method is fairly straightforward. The next question is how one can arrive at a reasonable and supportable macroeconomic forecast.

There are three different ways in which one can justify a reasonable forecast. One could use a baseline forecast such as the one produced by Moody's Analytics. Alternatively, one can use a set of scenarios that cover economic expansions and recessions and assign a probability weight to each scenario. The expected credit loss would be a probability-weighted sum of the expected credit losses on the set of scenarios. A third possibility is the use of a full-blown Monte Carlo simulation of the economic scenarios. In this method, one could calculate the loss for each scenario and calculate the average or expected value over the entire set of randomly simulated scenarios.

All three methods ensure that the calculations are done in an "average" or "expected" sense, as opposed to performing the calculations on stress or extreme scenarios. The use of a small set of probability-weighted scenarios, as opposed to a single baseline forecast, can help address the effect of any nonlinearities in the loss models while limiting the complexity of forecasting scenarios.

Modeling with Little Performance History

Not all financial institutions have a long enough performance history or high-quality loan-level data to build or calibrate loan-level models. Since the ASU requires that the models consider the historical performance of the reporting institution, we need to consider a few options depending on the quality and quantity of available data.

When we talk of the data used for building the models, we need to consider two dimensions. The first is the cross-sectional dimension which determines how rich the data is in relation to: loan terms and conditions such as different types of mortgage products, LTV distribution, interest rates on the mortgages; borrower characteristics such as FICO scores and income and employment verification; geographic distribution; and other variables such as the

> When we build a loan-level econometric model, we naturally separate out and capture the effects of macroeconomic drivers and loan and borrower characteristics.

type of property and distribution across vintages. The second is the time dimension which defines the length of the performance history and the availability of dynamic variables such as outstanding balance, delinquency status, interest rate, default and prepayment status, and realized losses.

The cross-sectional information defines the domain of applicability of the model. For example, if historical lending has been over a narrow range of FICO scores or origination LTVs, applying the model to a FICO or LTV value outside the range may be problematic. Similarly, if lending is limited to a certain geographic region of the US, applying a model built with this data to lending in other regions may be hard to justify. Data along the time dimension helps us account for business cycles containing economic expansions and recessions. Knowing how the mortgages behaved during the recent financial crisis helps us tease out the relationship between the default rate and large declines in home prices or high levels of unemployment rates. If we only had performance history of a few years when home prices were rising and the unemployment rate was falling, we will have to extrapolate the behavior of the models to periods that may contain a fall in home prices or a rise in unemployment rates.

This presents us with a few choices for building and implementing models. For example, one could build a model using an industrial-strength dataset that spans the entire US, covers different loan and borrower characteristics, and has a sufficiently rich performance history. If the reporting institution such as a bank does not have any historical data, either because the data was not collected in the past or the bank has started lending only recently, one has no choice but to use the model built using industry data as a proxy for the bank's estimated credit losses.

If, on the other hand, the bank has a limited data history, we would not be able to infer the dependence of the default rates, prepayment rates, or LGD from this data. However, we could infer this from the model built using industry data while refitting or calibrating the model to the bank's data. In other words, we could use some of the model coefficients from the industry model, but recalculate the remaining coefficients from the bank's data. In this manner, we capture the economic cycles as well as the bank's underwriting using a combination of the two datasets.

As a third possibility, the bank may have a rich and long enough data history. In that case, the bank may choose to build a model exclusively using its own data. This ensures that the models use the bank's performance history and are tuned to the bank's underwriting standards.

> The use of a small set of probability-weighted scenarios, as opposed to a single baseline forecast, can help address the effect of any nonlinearities in the loss models while limiting the complexity of forecasting scenarios.

Using Models on Little or Unreliable Data

The FASB received feedback from small financial institutions, such as community banks and credit unions, that the implementation of the ASU could be complex. Several financial institutions do not have reliable loan-level data to even make use of a standard loan-level model. In this case, we need to explore what options such institutions may have to calculate expected credit losses.

Consider a situation in which the loan-level model uses several fields, but a credit union only has a few pieces of information for each loan. For example, this information could be limited to original LTV, vintage, type of mortgage, and FICO score at origination. More details such as the type of property or the level of income and employment documentation, although used by a standard model, are not recorded by the credit union. There are two possibilities: one can apply typical, mean, or median values of the unknown factors to the loan-level model, or one can consider reasonable distributions of the unknown factors to arrive at an estimate of the uncertainty in the credit loss.

Consider another example of lack of quality loan-level data. Suppose a credit union only has a few pieces of information at an aggregate level for different segments of its portfolio and the total exposure for each segment. One may know that the average FICO score of fixed-rate loans is 650, the average LTV at origination is 85, and the total exposure is $50 million. Again, as in the previous example, one can use the known data along with estimates, typical values, or ranges for the other data fields to estimate the credit losses for each segment separately. By knowing the total exposure, we can arrive at the expected credit loss for each segment.

Conclusion

This paper shows how a loan-level approach can be used to estimate the expected credit losses over the life of a loan. It addresses a few of the items in the implementation of this approach. With the use of appropriately built and calibrated models, the method can be used not only for accounting for credit losses, but also in risk management and stress testing.

Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, National Credit Union Administration, and Office of the Comptroller of the Currency. "Joint Statement on the New Accounting Standard on Financial Instruments – Credit Losses." June 17, 2016.

Financial Accounting Standards Board. "Financial Instruments – Credit Losses (Topic 326)." FASB Accounting Standards Update. June 2016.

WHAT DOES THE NEW IMPAIRMENT STANDARD MEAN FOR STRUCTURED FINANCE HOLDINGS?

By Vainius Glinskis and David Kurnov

The new current expected credit loss standard affects more than just loan books. Under the new update, expected credit loss is recorded through an allowance for loan and lease losses in the financial statements. In contrast to the current "incurred loss" accounting method, the new CECL model requires forward-looking metrics that forecast credit losses throughout the life of a financial asset. Three groups of financial assets are affected: assets carried at amortized cost, purchased credit-deteriorated assets, and available-for-sale securities. The standard presents some unique challenges for structured finance investors due to the complicated and diverse nature of structured bonds. These include gathering of current data, projecting future performance, and mapping potential effects on triggers. Lastly, while the standard does not advocate any particular methodology, there are advantages to a discounted cash flow approach.

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David Kurnov
Senior Director,
Financial Engineering

David manages global operations for the Structured Finance Valuations & Advisory group at Moody's Analytics. His team develops and implements analytical models for valuing and stress testing securities across structured asset classes and provides advisory support for risk analysis and regulatory submission. David has a BS in economics from The Wharton School and a BSE in computer science from the School of Engineering at the University of Pennsylvania.

Introduction

In June 2016, the Financial Accounting Standards Board (FASB) released Accounting Standards Update (ASU) 2016-13, which changed the method of accounting for credit loss from an incurred loss approach to a projected loss approach. Expected credit loss (ECL) will need to be calculated on the day of purchase or origination and will need to reflect lifetime loss. At each reporting date, ECL calculations will have to combine historical data, current financial conditions, and future outlooks.

The ASU specifically addresses three different kinds of financial assets that will all be affected differently. They include held-to-maturity (HTM) securities, available-for-sale securities (AFS), and purchased financial assets with credit deterioration (PCD).

Held-to-Maturity Securities

The new current expected credit loss (CECL) model will only apply to financial assets measured at amortized cost (AC) and certain off-balance sheet items. More specifically, this includes HTM debt securities, loans, loan commitments, financial guarantees, and net investments in leases, as well as reinsurance and trade receivables.

Financial assets that fall within this scope will need to be pooled together based on similar credit risk characteristics. This is a deviation from the old standard which did not require pooling. This new requirement provides certain challenges, such as creating pooling methodologies and projecting losses for pools of assets instead of individually. This new methodology could generate some probability of default (PD) even for AAA-rated assets on a pooled or collective basis where there might be none on an individual basis.

All losses will be recorded the day of purchase or origination, and the allowance will be based off AC. The allowance will be affected by credit enhancements, which may limit losses. Depending on the nature of the collateral, the fair value (FV) of backing collateral can be reasonably assumed to be recoverable. Credit-enhancing derivatives will only affect ECL when they are embedded in the financial asset (i.e., they would travel with the asset when sold).

When all commercially available means to collect a loan balance are exhausted, the asset is written down to reflect a more permanent credit loss. However, recoveries are recorded when unexpected cash is received.

There are no specific models the ASU requires, but some examples include expected loss rate, vintage analysis, and discounted cash flow.

Available-for-Sale Securities

AFS securities do not measure ECL based on the CECL model. Instead, they use a modified other-than-temporary impairment (OTTI) approach, which requires a discounted cash flow approach. The new method no longer depends on the length of time an asset has been impaired and does not include a minimum threshold for losses. In this regard, the other-than-temporary aspect of the approach has been discontinued. Figure 1 compares the accounting implications of the legacy OTTI methodology with the new impairment approach, while Figure 2 provides an example of the change in calculations. For AFS securities, expected credit loss is measured whenever fair value (FV) falls below amortized cost. ECL no longer reduces amortized cost basis; instead, it is recorded in a contra account which is reassessed every reporting period and can be revised up. This means improvements in ECL will be immediately realized. This will also cause more volatility in ECL reporting. Unlike with HTM assets, pooling of securities is not allowed; assets are assessed on an individual level. Changes in FV that are not attributable to credit loss are still reported in other comprehensive income. Figure 3 shows a comparison of HTM and AFS treatment.

Purchased Financial Assets with Credit Deterioration

PCDs are assets that have more than insignificant credit deterioration since origination. What constitutes a significant credit deterioration is not explicitly defined, though credit ratings or PD could be used. A PCD is grossed up in value from FV by the amount of expected credit loss. The residual (interest-related) premium or discount is then amortized over time. The ECL calculation has to be reassessed each reporting period. The initial credit loss is reported on the balance sheet, whereas normally it would be reported in the profit and loss statement.

How Structured Finance Portfolios are Affected

Projecting credit losses for structured security portfolios can be very tricky because characteristics of securities can vary widely, even within the same asset class and vintage. These unique traits highlight the importance of understanding details of each structure, found in deal documents, surveillance reports, and other reports. These are some of the unique challenges:

» SF deals can have complex structures, with various embedded instruments to manipulate the distribution of underlying cash flows.

» Certain adverse credit shocks and events can increase the credit risk of certain tranches,

Figure 1 Comparing the old OTTI and new impairment calculations

	Old OTTI	New Impairment Calculation
Credit loss is temporary	Not reported	Reported
Credit loss is marginal	Not reported	Reported
Asset becomes less risky	Credit loss not revised	ECL revised

Source: Moody's Analytics

Figure 2 Example of impairment calculations

	Old Method	New Method	Comments
For an AFS security with improvement in credit risk	$2,455,000	$1,836,000	Under this scenario, the new method allows a revision upwards after expected credit loss improves.
For an AFS security with little impairment	$0	$12,000	Under this scenario, the new method requires any amount of impairment to be recorded, even if it is small.
For a HTM security with $0 incurred loss	$0	$654,000	Although there has been $0 incurred loss, projecting ECL into the future generates a calculated impairment allowance.
For two firms holding the same amount of the same security under HTM	$1,280,000/$1,280,000	$1,256,000/$1,312,000	Under the old method, the two firms should report the same incurred loss, but when projecting ECL under the new method, the two firms may have different models and scenarios generating their impairment calculations. This creates different impairment outputs.

Source: Moody's Analytics

Figure 3 Comparison of held-to-maturity and available-for-sale securities

	AC Greater Than FV	AC Less Than FV	Pooling of Assets?
HTM	Lifetime ECL	Lifetime ECL	Yes
AFS	Lifetime ECL	No ECL	No

Source: Moody's Analytics

but they can also trigger events that make senior bonds even less risky. For example, if a deal's payment structure changes from pro rata to sequential, then the most senior bonds are paid before other tranches, improving the chance their contracted payments are received.

» Each SF deal is backed by a unique and segregated pool. These pools of receivables generally would have been originated at different times with different concentrations, reflecting a unique risk profile.

» Collateral is not always purchased before bonds are sold (e.g., collateralized loan obligation (CLO) ramp-up periods). Certain asset classes (e.g., CLOs, credit cards, and student loans) could gain and lose collateral as the deal progresses (e.g., reinvestment or replenishment periods).

Using Discounted Cash Flow Models

ASU 2016-13 does not require any specific methodology for the CECL model but offers examples such as expected loss rate, vintage analysis, and discounted cash flow (DCF). DCF models are the most defensible because they have an expansive set of inputs which generates robust results. These models rely on blended scenarios that larger banks can reuse from Comprehensive Capital Analysis and Review (CCAR) and Dodd-Frank Act Stress Test (DFAST) models (e.g., bank-specific baseline scenario). The standard requires incorporation of reasonable forward-looking assumptions, but a single scenario may miss crucial loss outcomes for SF securities. Blended scenarios that use at least one downside case can better capture losses for SF securities. This applies especially for mezzanine/junior tranches on a loss cliff. SF deals often have contingent characteristics, such as triggers that depend on credit quality. Small changes in economic assumptions could change whether a contingent characteristic is triggered or not. This may have a large effect on the credit quality of a tranche, as a deal might change from a pro rata waterfall structure to one that is sequential. It is important to understand the possibility of these effects and their impacts so they can be properly accounted for in ECL calculations.

SF deals also incorporate other market-based optionality inherent in deals, such as call options, where a case-by-case analysis may need to be performed, for instance, for call likelihood. In some cases, an assessment of this risk may not be possible if stated methodologies do not address these factors. Tranche seniority, thickness, and homogeneity of collateral pool also have large effects as to how different tranches within a deal will perform under different scenarios.

Another reason to use a DCF approach is that it is transparent and dynamically customized. Customization allows an institution to change how it approaches expected loss calculation based on an agreed-upon vision of the future economy.

The downside to DCF models is that they require abundant resources to run cash flow projections, such as credit models, performance data, and economic scenarios. This might limit DCF model use for smaller institutions for which such technical analysis is not feasible.

Although DCF models are resource-intensive, they may be necessary to accurately project ECL for SF portfolios due to the complicated nature of SF securities. Because SF securities are structured in different ways, their risk profiles can differ from deal to deal. Risk may be concentrated at the beginning or end of the life of the deal, depending on the structure of the deal and the subordination of the tranche. Triggers also affect the credit risk of tranches differently based on an economic outlook of the future. DCF models capture the effects of the individual characteristics of each deal. Economic scenario inputs for DCF models can simulate the effects that triggers and other contingent characteristics have on the credit risk for each individual tranche. Thus, to accurately project losses for SF securities that contain various nuances, a DCF model is recommended.

> Projecting credit losses for SF portfolios can be very tricky because their characteristics can vary widely, even within the same asset class and vintage. These unique characteristics highlight the importance of understanding details of each structure.

Financial Accounting Standards Board. "Financial Instruments – Credit Losses (Topic 326)." FASB Accounting Standards Update 2016-13. June 2016.

CECL SURVEY RESULTS

By Michael McDonald and Seung Lee

In this article, we summarize the results of a Moody's Analytics survey conducted to assess US banks' preparations for CECL. The survey found that banks foresaw the most challenges in terms of data and modeling needs. Most banks expected to increase provisions as a result of CECL, but the effects on loan pricing were largely undetermined. At the time of survey, banks were generally focused on early preparation needs such as forming working groups, acquiring budget approvals, and developing timelines with full implementation planned for 2020 or 2021.

Michael McDonald and Seung Lee
Strategy and Analytics

Michael McDonald and Seung Lee are assistant directors on the Strategy and Analytics team of Moody's Analytics. They inform the broader organization of industry news, trends, and regulations, deliver insights into business performance, and guide long-term growth efforts with qualitative and quantitative evaluation.

Moody's Analytics conducted a survey to assess US banks' preparedness for the Financial Accounting Standards Board's (FASB's) Financial Instruments – Credit Losses (Topic 326) guidance, known as current expected credit loss (CECL). From June 2016 to August 2016, we conducted one-on-one discussions with representatives from 26 banks of varying asset levels to determine progress, main challenges, and planned investments surrounding CECL compliance.

The survey revealed these key points:

- Banks anticipated the most challenges in areas of data quality and quantity, as well as life-of-loan loss models. They anticipated fewer challenges concerning software, calculations, and reporting.
- Banks broadly expected to increase provisions as a result of CECL.
- More than half of the banks were already in early stages of preparation.

Scope of Survey

CECL compliance will be mandatory for nearly 6,100 US banks. As shown in Figure 1, the vast majority of these banks have under $5 billion in assets and are located in the South and Midwest. We spoke to representatives from 26 of these banks whose main asset classes, defined as asset classes making up more than 20% of their loan portfolio, included residential real estate (RRE), commercial real estate (CRE), and commercial and industrial (C&I) sectors. Survey participants typically had job functions related to credit, accounting, risk, and finance. Reflecting the total industry landscape, participating banks were generally stationed in the South and Midwest and had assets under $5 billion. Participants' complete characteristics are shown in Figure 2.

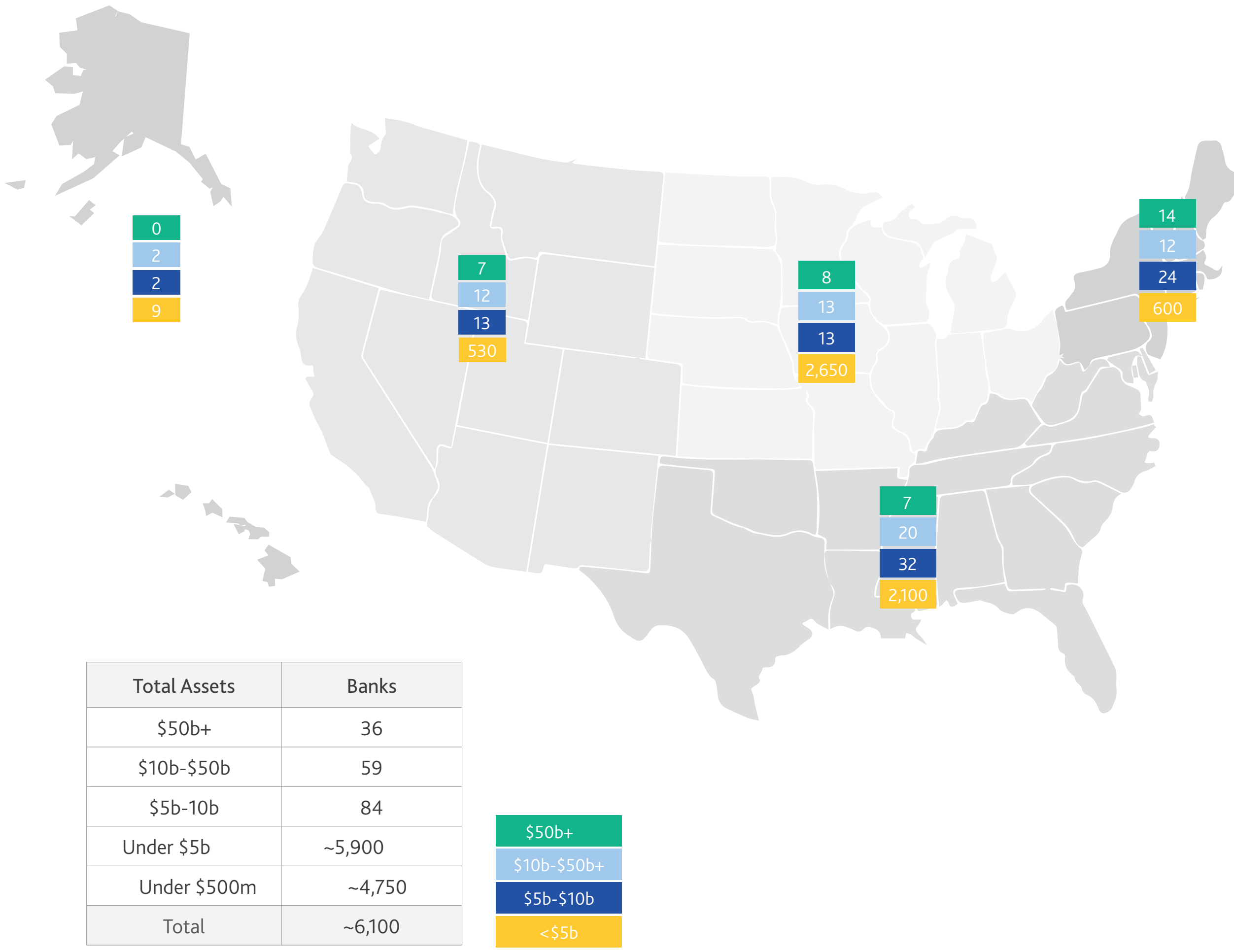
Effects on Provisions and Pricing

CECL compliance is expected to affect banks' provisions and some banks' loan pricing, as shown in Figure 3 and Figure 4, respectively.

The majority of banks surveyed expected to increase their overall provisions as a result of CECL compliance. This is in line with CECL's goal of ensuring adequate reserves and minimizing emergency provisioning, which can amplify an economic downturn like it did during the Great Recession.

Notably, 12% of respondents expected their provisions to decrease or remain flat. CECL may reduce reserves on some portfolios, such as those with C&I loans, because they are short-dated. Additionally, some banks may have already had appropriate or surplus reserves

Figure 1 Banks subject to CECL by location and total assets



Total Assets	Banks
$50b+	36
$10b-$50b	59
$5b-10b	84
Under $5b	~5,900
Under $500m	~4,750
Total	~6,100

Source: FDIC

because of their qualitative (Q) factors. Banks use Q factors to account for differences between past conditions, on which models are based, and existing conditions. When a bank's Q factor reflects an overestimate of the negative effect of conditions like unemployment rates or interest rates, the bank has likely over-reserved.

CECL compliance will provide banks with a clearer view of expected life-of-loan loss, which may prompt banks to adjust their loan pricing accordingly. While half of respondents were unsure of whether CECL would have an effect in this regard, nearly a third said they expected it to impact their loan pricing.

Anticipated Challenges

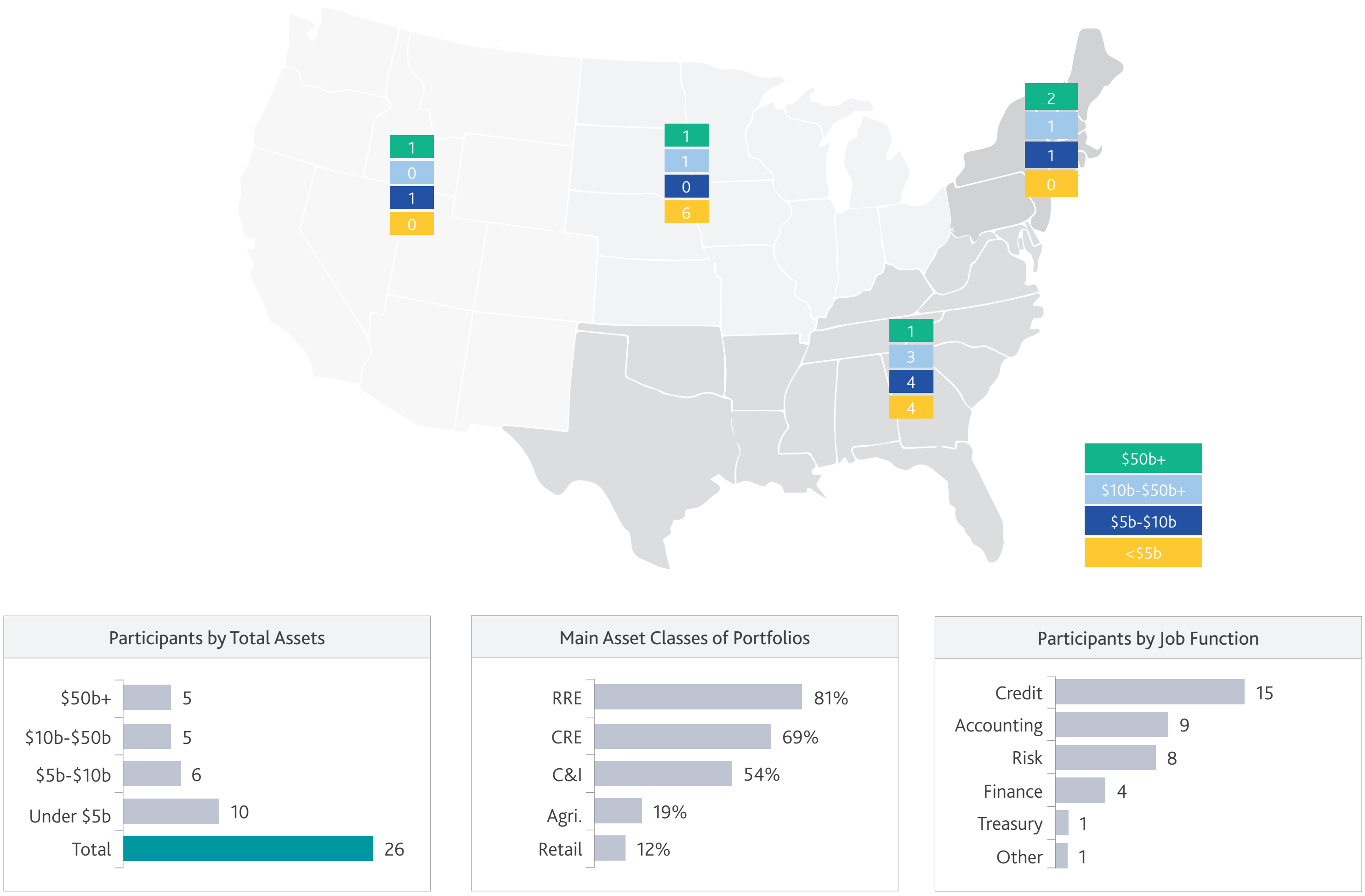
Banks of all sizes anticipated challenges converting to CECL, with smaller banks foreseeing significantly more challenges than larger ones. Banks faced different challenges, and therefore anticipated different investments, based on their size. Anticipated challenges are summarized in Figure 5.

All but the largest banks foresaw challenges related to data. Those with under $50 billion in assets often lack sufficient historical data, lack the right types of data, or cannot retrieve the data from their core systems.

These data challenges – along with an absence of internal modeling teams and in-house economists – commonly lead to modeling obstacles. Almost all surveyed banks, with the exception of some of the largest ones, anticipated challenges in applying life-of-loan loss models.

From a software and calculations perspective, foreseen challenges depended on how banks' allowance for loan and lease losses (ALLL) processes are set up. Larger banks, those with assets over $50 billion, are more likely to have internal capabilities to complete calculations.

Figure 2 Survey participants by geographic location, total assets, main asset classes, and job function



Source: Moody's Analytics

Those with lower asset levels, under $5 billion, planned to use outside vendors to circumvent potential software and calculation issues. Mid-sized banks – those with assets of $5 billion to $50 billion and that used more simplistic ALLL processes, such as methods utilizing internally developed Excel spreadsheets – expected challenges with the calculations, as their processes are likely to change significantly under CECL.

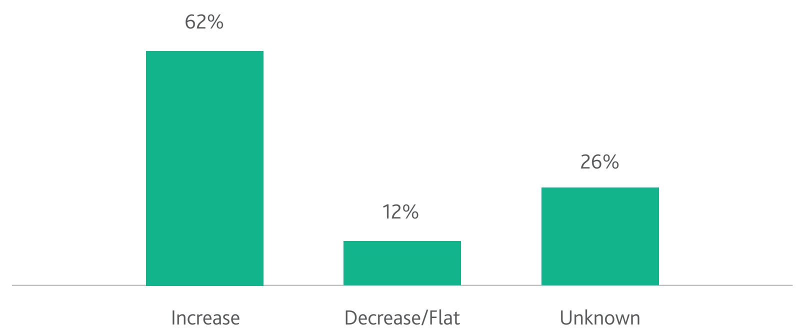
With leaner organization structures, banks with under $5 billion in assets expected to see the smallest impact on reporting as a result of CECL. On the other end of the spectrum, banks with over $50 billion in assets have the greatest obligation for accurate and thorough reporting because of a typically high number of stakeholders. These banks anticipated more significant impacts to reporting to help understand and justify the impact to provisions. And because they tended to have underdeveloped reporting capabilities, reporting on CECL was expected to pose challenges. Banks falling between the two extremes unsurprisingly had mixed responses.

Where challenges were expected or capabilities didn't exist, banks planned to invest in expanding or establishing internal capabilities or enlisting the help of external vendors.

Timelines and Preparedness Levels

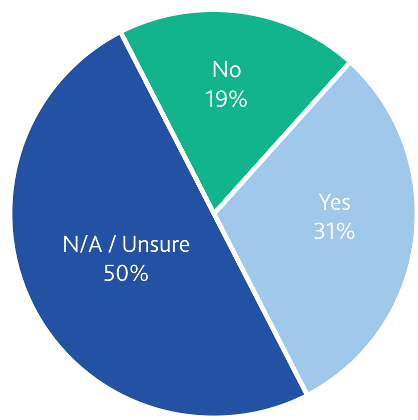
At the time of survey, banks were in early stages of CECL planning and preparation. Banks that need to file with the Securities and Exchange Commission (SEC) must adopt CECL by 2020, whereas non-SEC filers have until 2021 to become compliant. Although SEC filers have more compressed timelines, non-SEC filers are fully aware of the challenges that come with

Figure 3 Expected impact on banks' provisions



Source: Moody's Analytics

Figure 4 Responses regarding whether CECL will affect loan pricing



Source: Moody's Analytics

CECL; both groups, therefore, are in similar preparation stages.

More than half of banks surveyed reported that they had already spoken with auditors for early preparation, and more than a quarter had already engaged vendors. Early vendor discussions were focused on cost estimates, software integration capabilities, and expected timelines for completed solutions. At the time of survey, most banks were focused on forming working groups, acquiring budget approvals, and developing timelines by early 2017.

SEC-filing survey respondents stated they would focus on implementation between mid-2017 and the end of 2019. Banks with more than $50 billion in assets expressed minimal interest in early adoption, which is permitted for fiscal years beginning after December 15, 2018. Subsequently, most respondents planned to perform parallel runs between mid-2018 and the end of 2020, with 69% confirming that parallel runs would be necessary.

The timeline for non-SEC filers lags by about a year. In general, these banks planned to complete initial preparation steps by early or mid-2018, complete implementation by 2020, and conduct parallel runs by the end of 2021. Banks' anticipated high-level timelines are summarized in Figure 6.

Banks' Opinions and Reactions

As banks continue to learn about CECL's requirements, the path forward does not come without concerns. Some survey participants believe the FASB may have made the standard overly complex.

"The CECL standard has gone too far," according to one CCAR bank, "and current practices, which must now be changed, could have incorporated future events more simply."

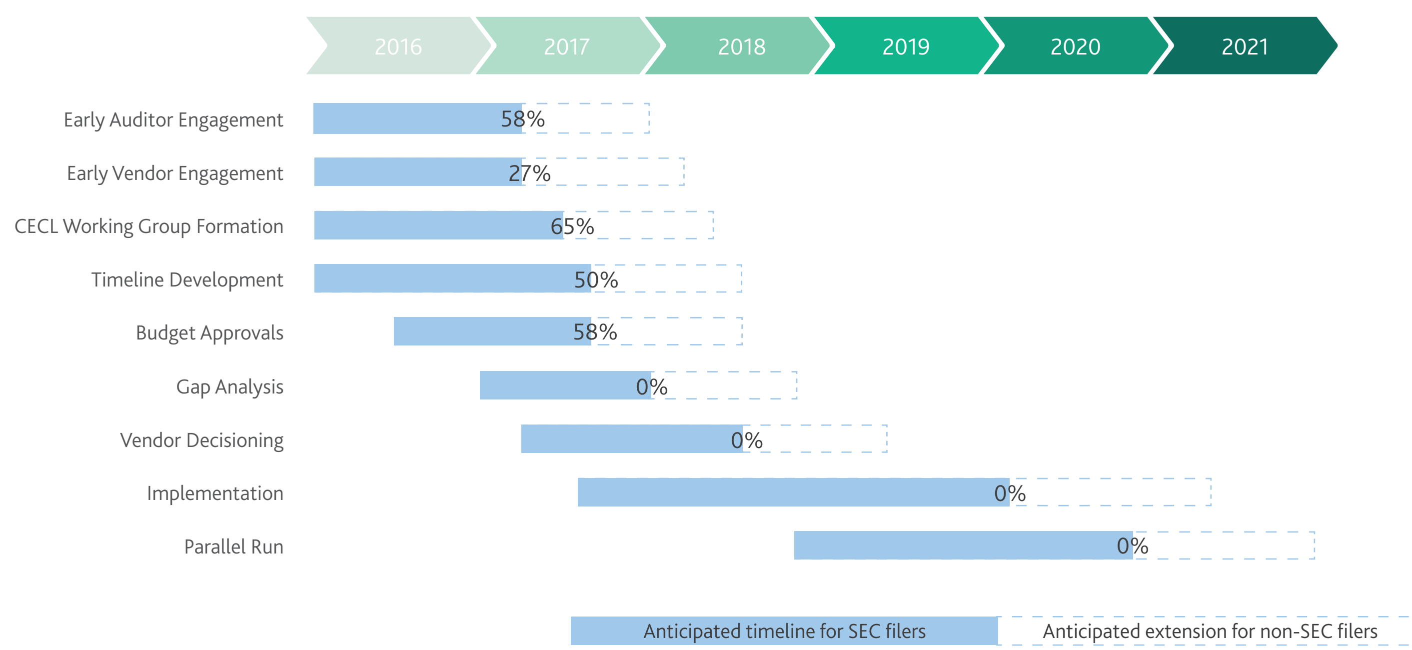
Figure 5 Areas in which banks anticipate challenges

✓ Challenges anticipated ✗ No challenges expected — Mixed responses

	<$5b	$5b-$10b	$10b-$50b (DFAST)	$50b+ (CCAR)
Data	✓	✓	✓	✗
Life-of-Loan Loss Models	✓	✓	✓	—
Software/Calculations	—	✗	—	—
Reporting	✗	—	—	✓

Source: Moody's Analytics

Figure 6 Anticipated high-level timeline for CECL compliance, and the percent of respondents that already began each step



Source: Moody's Analytics

Some smaller banks question the applicability of CECL to rural/community banks.

"CECL is not necessary for a smaller bank," according to a private community bank. "Smaller banks should have a good handle on their customers and risk levels as a rural/community bank."

Even with CECL's challengers, many respondents acknowledged the need to change from an incurred loss approach to an expected loss approach, and that CECL may create opportunities for improved business practices.

"CECL forces institutions to put more rigor around qualitative methods and is practically helpful," said one respondent.

Another acknowledged, "CECL is seen as an opportunity to streamline and eliminate risk."

While respondents' opinions and reactions to CECL vary, the standard poses real challenges for organizations of all sizes. Over the next 12 to 24 months, banks will continue to progress toward becoming CECL-ready by continuing to assess their current capabilities and close gaps as needs become clear.

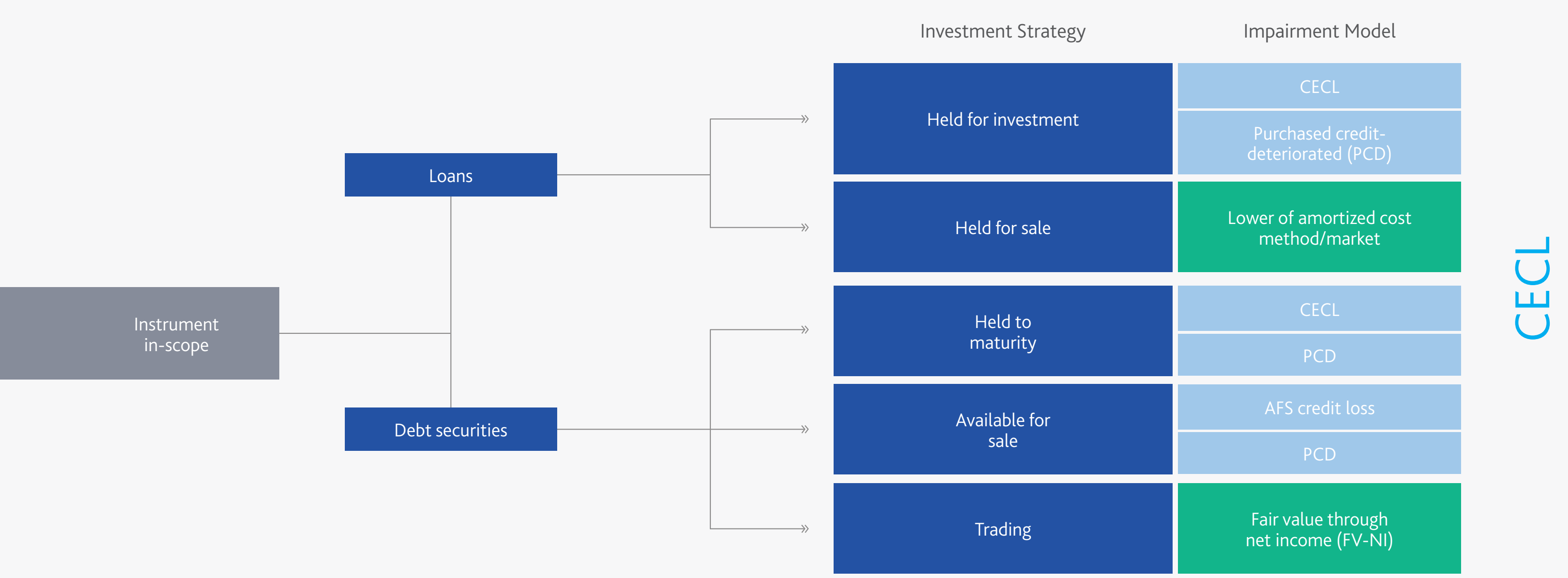
CECL VS. IFRS 9

By Emil Lopez

COMPARISON OF IMPAIRMENT APPROACHES UNDER IFRS 9 AND CECL

		CECL	IFRS 9
FIVE MAJOR SIMILARITIES	Instruments in Scope for Impairment	» Financial assets at amortized cost and fair value through other comprehensive income (FVOCI) » Lease receivables » Financial guarantee contracts » Loan commitments » Reinsurance receivables	» Financial assets at amortized cost and FVOCI » Lease and trade receivables » Financial guarantee contracts » Loan commitments with obligation to extend credit » Contract assets within scope of IFRS 15
	Measurement Objectives	» Reflect management's best estimate of expected credit losses, based on information about past events, current conditions, and supportable forecasts of future economic conditions	» Reflect an unbiased and probability-weighted amount, determined by evaluating a range of possible outcomes » Incorporate the time value of money » Utilize reasonable and supportable information, available without undue cost, about past events, current conditions, and forecasts of future economic conditions
	Treatment for Undrawn Loan Commitments	» Must estimate credit losses over the full contractual period for which the entity is exposed to credit risk, accounting for the likelihood of funding and expected losses (EL) on future funding » May be impacted by: the ability to unconditionally cancel the commitment; and the lead time for cancellation to become effective	» For undrawn loan commitments that are irrevocable, a credit loss is the present value of the difference between (a) the contractual cash flows due to the entity if the holder of the loan commitment draws down the loan, and (b) the cash flows the entity expects to receive if the loan is drawn down
	Treatment for Renewable Loans	» Impairment must be calculated based on contractual life, despite possibility for renewal	» Impairment must be calculated based on contractual life, despite possibility for renewal
	Individual Loan Impairment Assessments	» Individual loan impairment assessment still allowed » Impairment status remains a unique credit characteristic that is sufficiently significant to warrant exclusion of a loan from a pool of other similar unimpaired loans » If individually assessed, must exclude from collective assessment	» Individual loan impairment assessment still allowed » If individually assessed, must exclude from collective assessment

Sources: IASB, FASB



FIVE MAJOR DIFFERENCES

	CECL	IFRS 9
Practical Expedients	» 1) Collateral-dependent loans, and 2) financial assets with continuous adjustments to amount of securing collateral » Can record EL as the difference between amortized cost and collateral's fair value » For periods beyond supportable forecasts, can revert to historical loss experience	» For trade receivables with a significant financing component, a simplified model with an allowance of lifetime EL may be used, rather than the multi-stage approach » 30 days and 90 days past due can be used to trigger stage 2 and 3 classification, respectively; these presumptions are rebuttable » Instruments considered to have "low risk" can remain in stage 1
Instrument Stage Classification	» Impairment for all instruments is based on lifetime expected credit loss (ECL)	» Stage 1: 12-month ECL at recognition » Stage 2: Lifetime ECL when significant deterioration in credit quality is observed since initial recognition unless credit risk is low » Stage 3: Lifetime ECL if instrument is impaired » Instruments can migrate across stages
Impairment Model for Available-for-Sale (AFS) Securities	» Improvements in other-than-temporary impairment (OTTI) model in ASU 320 for securities where there is not an intent to sell or more-likely-than-not requirement to sell » Estimated credit loss for these securities recorded as an allowance » Improvements in credit risk may be recovered through allowance adjustment » Removed concept of "other than temporary"	» OTTI definition and AFS classification do not exist under IFRS 9 » Based on instrument classification framework, these are likely to be categorized as fair value through profit or loss (FVPL) or FVOCI » Single impairment model
New Disclosures	» Public entities must disclose credit quality indicators by year of origination (vintage) over five years » Public non-Securities and Exchange Commission (SEC) filers only required to provide three years upon adoption, adding another year of information over time until they reach five years	» Changes in ECL due to (among others): – Stage migration – New originations/run-off – Changes to modeling assumptions
Implementation Deadline	» SEC registrants: Jan. 1, 2020 » Non-SEC registrants: Jan. 1, 2021 » Early adoption: Permitted beginning Jan. 1, 2019	» Jan. 1, 2018 » Early adoption: Varies by country » Insurance companies have option to defer until 2021

THE IFRS 9 IMPAIRMENT MODEL AND ITS INTERACTION WITH THE BASEL FRAMEWORK

By Julien Temim

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Julien works in the Stress Testing & IFRS 9 Advisory Services team as a business analyst and consultant. In his role, he supports lead analysts and engagement managers in their efforts to design and deliver customized solutions to clients. On previous engagements, his main focus was on analyzing regulatory-oriented issues, conducting research and outlining requirements, documenting client current state processes, and conducting gap analysis. Julien has a BA in government and strategy from the Interdisciplinary Centre Herzliya and an MSc in international relations from the University of Edinburgh.

He would like to thank Nadja Roos, Maria Chvartatskaya, Manuele Iorio, and Wasim Karim for their valuable feedback.

The impending implementation of the IFRS 9 impairment standard offers unique challenges and opportunities in integrating the new allowance calculation process with existing capital calculation and reporting requirements under Basel III. This article explores the growing interaction between risk management and accounting in relation to credit risk modeling approaches, capital ratios, and provisions calculations, as well as data management and governance in preparation for IFRS 9.

Introduction

In the wake of the 2008 financial crisis, the International Accounting Standards Board (IASB) in cooperation with the Financial Accounting Standards Board (FASB) launched a project to address the weaknesses of both International Accounting Standard (IAS) 39 and the US generally accepted accounting principles (GAAP), which had been the international standards for determining financial assets and liabilities accounting in financial statements since 2001.

By July 2014, the IASB finalized and published its new International Financial Reporting Standard (IFRS) 9 methodology, to be implemented by January 1, 2018 (with the standard available for early adoption). IFRS 9 will cover financial organizations across Europe, the Middle East, Asia, Africa, Oceana, and the Americas (excluding the US).

For financial assets that fall within the scope of the IFRS 9 impairment approach, the impairment accounting expresses a financial asset's expected credit loss as the projected present value of the estimated cash shortfalls over the expected life of the asset. Expected losses may be considered on either a 12-month or lifetime basis, depending on the level of credit risk associated with the asset, and should be reassessed at each reporting date. The projected value is then recognized in the profit and loss (P&L) statement.

Most banks subject to IFRS 9 are also subject to Basel III Accord capital requirements and, to calculate credit risk-weighted assets, use either standardized or internal ratings-based approaches. The new IFRS 9 provisions will impact the P&L that in turn needs to be reflected in the calculation for impairment provisions for regulatory capital. The infrastructure to calculate and report on expected loss drivers of capital adequacy is already in place. The data, models, and processes used today in the Basel framework can in some instances be used for IFRS 9 provision modeling, albeit with significant adjustments. Not surprisingly, a Moody's Analytics survey conducted with 28 banks found that more than 40% of respondents planned to integrate IFRS 9 requirements into their Basel infrastructure.[1]

Arguably the biggest change brought by IFRS 9 is incorporation of credit risk data into an accounting and therefore financial reporting

1 Gea-Carrasco, 2015.

process. Essentially, a new kind of interaction between finance and risk functions at the organization level is needed, and these functions will in turn impact data management processes. The implementation of the IFRS 9 impairment model challenges the way risk and finance data analytics are defined, used, and governed throughout an institution. IFRS 9 is not the only driver of this change. Basel Committee recommendations,[2] European Banking Authority (EBA) guidelines and consultation papers,[3] and specific supervisory exercises, such as stress testing and Internal Capital Adequacy Assessment Process (ICAAP), are forcing firms to consider a more data-driven and forward-looking approach in risk management and financial reporting.

Accounting and Risk Management: An Organization and Cultural Perspective

The implementation of IFRS 9 processes that touch on both finance and risk functions creates the need to take into account differences in culture, as well as often different understandings of the concept of loss in the two functions.

The finance function is focused on product (i.e., internal reporting based on internal data) and is driven by accounting standards. The risk function, however, is focused on the counterparty (i.e., probability of default) and is driven by a different set of regulations and guidelines. This difference in focus leads the two functions to adopt these differing approaches when dealing with impairment:

- The risk function uses a stochastic approach to model losses, and a database to store data and run the calculations.
- Finance uses arithmetical operations to report the expected/incurred losses on the P&L, and uses decentralized data to populate reporting templates.

In other words, finance is driven by economics, and risk by statistical analysis. Thus, the concept of loss differs between teams or groups: A finance team views it as part of a process and analyzes loss in isolation from other variables, while the risk team sees loss as absolute and objectively observable with an aggregated view.

IFRS 9 requires a cross-functional approach, highlighting the need to reconcile risk and finance methodologies. The data from finance in combination with the credit risk models from risk should drive the process. The risk function runs the impairment calculation, whilst providing objective, independent, and challenger views (risk has no P&L or bonus-driven incentive) to the business assumptions. Finance supports the process by providing data and qualitative overlay.

Credit Risk Modeling and IFRS 9 Impairment Model

Considering concurrent requirements across a range of regulatory guidelines, such as stress testing, and reporting requirements, such as common reporting (COREP) and financial reporting (FINREP), the challenge around the IFRS 9 impairment model is two-fold:

- **Models:** How to harness the current Basel-prescribed credit risk models to make them compliant with the IFRS 9 impairment model.
- **Data:** How (and whether) the data captured for Basel capital calculation can be used to model expected credit losses under IFRS 9.

Figure 1 outlines the key differences between the Basel credit risk models and the IFRS 9 impairment model.

As Figure 1 highlights, the Basel III models can be used for IFRS 9 under the condition that significant adjustments are made, such as:

- Removal of the regulatory-driven components (e.g., regulator floors and observation periods)
- Correction for the point in the economic cycle for the TTC measures
- Adjustment of the model to the expected life of the financial instruments

The modeling approach for the key risk parameters will be affected by the incorporation of forward-looking, credible, and robust economic scenarios into accounting models. Additionally, banks will need to compensate

2 See BCBS (2013) and BCBS (2015).

3 See CEBS (2010) and EBA (2015).

Figure 1 Key model parameter differences of Basel and IFRS 9 models

	Key risk parameter	Basel III	IFRS 9
Probability of Default (PD)	Measurement standard	Average of default within the next 12 months	Depending on the asset, the PD measures either for the next 12 months (stage 1) or for the remaining life of the financial instrument (stages 2 and 3)
	Period of measurement (look-back period)	Estimates based on long-run average default rate, ranging from "point-in-time" (PIT) to "through-the-cycle" (TTC)	Estimates based on PIT measures, at the reporting date, of current and expected future conditions reflecting future economic cycles
Loss Given Default (LGD)	Intention of estimate	"Downturn" LGD to reflect adverse economic scenarios	"Current" or "forward-looking" LGD to reflect impact of economic scenarios
	Collection cost	Considers both direct and indirect cost associated with collection of the exposure	Only considers cost directly attributable to the collection of recoveries
	Discount rate	Based on weighted average cost of capital or risk-free rate	Depends on the type of financial instrument but is broadly based on effective interest rate
	Period of observation	Minimum five years for retail exposures, seven years for sovereign, corporate, and bank exposures	No specific requirements about observation period or collection of historical data used
Exposure at Default (EAD)	Intention of estimate	"Downturn" EAD to reflect what would be expected during a period of economic downturn	Considers all the contractual terms over the lifetime of the instrument
	Period of observation	Minimum five years for retail exposures, seven years for sovereign, corporate, and bank exposures	No specific requirements about observation period or collection of historical data used
Expected Loss/Expected Credit Loss (ECL)	Calculation	PD × LGD (loss rate) is applied to EAD	PD × PV of cash shortfalls represents a probability-weighted estimate of credit losses
	Economic assumptions	Reflects downturn LGD and EAD (factoring in macroeconomic stress conditions)	Reflects an unbiased probability-weighted amount, determined by evaluating a range of possible outcome

Sources: BCBS, IASB

for a lack of historical data by using expert overlays, vendor models, or external data pools. Overcoming the challenge of insufficient historical data, common in small and medium banks, increases the cost of implementing an IFRS 9 solution.

Under the current Basel framework, the following two approaches can be used for credit measurement to calculate regulatory capital:[4]

» The standardized approach (SA) allows the bank to measure credit risk in a standardized manner, assigning risk weights supported by external credit assessments.

» The internal ratings-based approach (IRB), which is subject to the explicit approval of the bank's supervisor, would allow banks to use internal rating systems for risk-weighted asset (RWA) calculation for credit risk. This includes measures for PD, LGD, EAD, and effective maturity (M). In some cases, banks may be required to use a supervisory value as opposed to an internal estimate for one or more of the risk parameters.

Depending on whether the standardized or advanced Basel approach is used, the bank will be able to leverage some of the data used by the Basel models to model IFRS 9 expected credit loss and encourage easier reconciliation of inputs for capital requirement and impairment calculations. Figure 2 presents some clarification.

For banks using the standardized and foundation IRB approaches, the challenge revolves around the level of data granularity and associated ratings, systems, and modeling capabilities. Overcoming these challenges will require investments for system upgrades, data gap

4 BCBS, 2006.

modeling, model development, and human resources.

According to a Moody's Analytics survey, more than 63% (consolidating the views from 28 banks) are planning to leverage existing IRB models for the credit loss impairment calculation.[5] Although significant adjustments need to be made, the impairment model proposed by the IASB brings accounting and regulatory standards closer.

The use of either of the two approaches influences the way regulatory capital is calculated, the treatment of provisions and expected credit losses, and the setting and composition of capital ratios.

Capital Ratio and Provisions

IFRS 9 requires an institution to immediately recognize a 12-month ECL from a financial asset at the first reporting date after origination, and create an allowance to cover such loss.[6]

The expected credit loss is to be covered by provisions, and unexpected loss is to be covered by capital. As a consequence, loss provisions will significantly increase under IFRS 9, thus reducing the equity and retained earnings available for Tier 1 capital, which in turn may reduce the Tier 1 capital ratio.

As outlined in the BCBS revised framework for the International Convergence of Capital Measurement and Capital Standards, the treatment of impairment provisions differs based on the credit measurement approach used by the institution:[7]

- The standardized approach will see a 1:1 impact on Core Tier 1 capital in case a loss has occurred, as the impact on retained earnings to cover the losses affects the availability of Tier 1 capital resources. However, in some circumstances, provisions can be included in Tier 2 capital subject to the limit of 1.25% of risk-weighted assets.
- Under the IRB approach, banks must compare the total amount of total eligible provisions (defined as the sum of all provisions that are attributed to exposures treated under the IRB approach) with the total expected loss amount as calculated within the IRB approach. There are then the following two scenarios:
  - If the expected loss is greater than the total eligible provisions, the surplus of expected loss over provision is reduced from the capital. The reduction is on the basis of 50% from Tier 1 and 50% from Tier 2.

Figure 2 Usability of the Basel modeling data for IFRS 9 purposes

	Mode of credit risk computation	IFRS 9 usability
Standardized Approach	Measurement of credit risk in a standardized manner, supported by external credit assessment informing asset's risk weights for regulatory capital calculation	Data is not complete or substantial enough to meet IFRS 9 modeling requirements
Foundation IRB	Own PD estimation and rely on supervisory estimates for other risk components for regulatory capital calculations	Data can be leveraged, under the condition that significant adjustments are made
Advanced IRB	Own PD, LGD, EAD estimates, and calculation of maturity (M) for regulatory capital calculations	Data can be leveraged, under the condition that significant adjustments are made

Sources: Tata Consultancy Services, Moody's Analytics

5 Gea-Carrasco, 2015.

6 Levy, et al, 2016.

7 BCBS, 2006.

- If the expected loss is smaller than the total eligible provisions, the difference is recognized in Tier 2 capital up to a maximum of 0.6% (limit subject to national discretion) of credit risk-weighted assets.

As of August 2016, the Basel Committee and prudential regulators are assessing the impact of IFRS 9 whilst banks are calling for a change in credit risk rules to account for the mismatch.[8] Figure 3 lists some options that could be considered by local regulators, depending on the situation.

Data Management and Governance

Moody's Analytics IFRS 9 survey, cited earlier, found that availability of granular data ranks highest when it comes to the difficulty of designing and implementing an IFRS 9 solution. For many institutions, this means that new data systems must be designed and implemented with the requisite governance, controls, and reconciliation capabilities to cope with IFRS 9 data granularity requirements.

BCBS 239 provides another example of how an existing framework may be used to facilitate risk and accounting reconciliation. Similar to data requirements for stress testing, the IFRS 9 impairment model calls for a robust and well-defined data governance framework, with the data infrastructure providing enough granularity, risk control standards, and transparency across the management of the data life cycle.

Those requirements will impact IFRS 9 qualitative disclosures, such as:

- Inputs, assumptions, and estimation techniques for estimating ECL
- Inputs, assumptions, and estimation techniques to determine significant increases in credit risk and default
- Input, assumptions, and techniques to determine credit impairment

An IFRS 9 implementation will involve a shift from often siloed-function data with no coordination, a lack of organizational oversight, and a fragmented IT structure, to a cross-functional approach to data with clearly defined data ownership and segmentation across the bank.

Figure 3 Potential prudential response

	Expected loss is smaller than the total eligible provisions	Expected loss is greater than the total eligible provisions
No change to regulatory capital treatment	No adjustment to Tier 1 capital; addition to Tier 2 capital, up to the limit	Additional Tier 1 capital to cover the allowance deficit
Symmetrical treatment	The excess amount of allowance is added back to Core Tier 1 capital	Additional Tier 1 capital to cover the allowance deficit
Accept accounting allowance	No adjustment to Core Tier 1 Capital	No adjustment to Core Tier 2 Capital

Sources: IFRS Foundation, Moody's Analytics

Conclusion

IFRS 9 implementation offers opportunities and challenges. Banks must centralize data from numerous sources, coordinate and manage a wide variety of models, evaluate changes in credit risk, and calculate expected credit losses and provisions accordingly. Banks also need to prepare and export data required by external accounting systems.

The IFRS 9 solution and its associated infrastructure should be able to integrate with

8 Hegarty, 2016.

other systems or stand alone to support the implementation of credit loss impairment calculations. It should have the following features:

- Transparency, control, auditability, traceability, and repeatability
- Comprehensive data management capabilities to reduce reconciliation burden
- Ability to automate the identification of higher-than-expected ECL amounts so they can be analyzed in more detail
- Industry-leading models for expected credit loss calculation and cash flow generation
- Model governance including a centralized EAD, PD, LGD
- Enterprise-wide software that integrates data, models, and reports, enabling institutions to scale while maintaining performance
- Seamless integration with accounting systems
- Reporting for business intelligence and financial disclosures with automated analysis of allowance volatility over multiple reporting dates

In the short term, the IFRS 9 impairment model puts extra pressure on institutions, might prompt a shift from the standardized approach to the more challenging IRB one, and encourages banks to address their data governance shortcomings and break internal silos. In the long term, the convergence between IFRS 9 and Basel III will improve risk management and bring greater integration with accounting practices. It will also provide stronger foundations for a more secured industry and improve confidence and transparency for all stakeholders in the market.

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Interview with Mark Almeida

PRESIDENT, MOODY'S ANALYTICS

The theme of this year's Risk Practitioner Conference is The Convergence of Risk, Finance, and Accounting. Why?

The Risk Practitioner Conference has evolved since its inception 11 years ago, and this evolution reflects the considerable change that has impacted banking and financial markets in this century. What started as a rather unique, regional seminar focused on innovations in credit risk has grown into an event that attracts risk, finance, and technology professionals from around the world. In response to the financial crisis, new regulatory forces and governance practices are driving dramatic change in financial institutions' management of risk. Stress testing programs implemented by regional banking regulators, new accounting standards, and more rigorous capital adequacy and liquidity risk requirements are bringing risk, treasury, and finance functions closer together. Because this is top of mind for financial institutions, we have organized our program accordingly.

Why is this theme important to Moody's Analytics?

We have long believed that financial institutions would inevitably leverage modern technology capabilities to undertake better, more precise, and more efficient risk management. This vision is at the core of what we do at Moody's Analytics. We believe that advanced quantitative analytics can have greater impact if they are integrated and made accessible across an enterprise – from a risk modeling professional to a front-line banker and to the CFO. Although responses to the spate of recent regulatory imperatives have been difficult and costly to implement, we believe that the investment made by banks and insurers to comply with such regulation will ultimately provide the means for better decision-making and enhanced operational oversight of financial institutions. Increasingly, we see that executives of financial institutions are recognizing this. While we're not there yet, the industry is clearly evaluating this convergence of risk and finance functions, and Moody's Analytics is eager to contribute to this process by facilitating dialogue among industry participants on these important topics.

What should participants expect at this year's conference?

This year's conference builds on what is now a well-established tradition, with sessions designed jointly by industry practitioners and Moody's Analytics subject matter experts. This results in a selection of topics that are of high priority for the industry. One enhancement that we're introducing this year is the organization of seminar streams by business function. We are planning four concurrent streams oriented toward technologists, finance and treasury professionals, credit risk managers, and specialists in quantitative risk. This structure will allow us to zero in on function-specific issues that are part of the broader industry themes. For example, we will discuss upcoming changes in impairment standards from multiple perspectives: methodology design and organizational design within the credit risk management stream, and technical architecture design within the technology stream. In a separate session, we will also solicit feedback from auditors and banking supervisors, who of course are the ultimate reviewers of any accounting standard implementation. Through this framework, we look forward to hosting a series of productive sessions that build on the ongoing conversations we have with market participants, all within a forum that brings these important issues to a larger and broader audience.

PRINCIPLES AND PRACTICES

THE FUTURE OF SMALL BUSINESS LENDING

By Avinash Arun, Nancy Michael, and Helene Page

In this article, we provide a summary of findings from our recent market research study on small business lending, which focused on the lending process and the challenges associated with banks' credit risk assessments. This article provides an overview of small business lending today, discusses challenges and emerging trends, and provides recommendations for addressing the challenges to create a more streamlined and automated lending process.

Avinash Arun
Associate Director, Senior Strategist

Avinash is a senior product manager in the Small and Mid-Market Enterprise (SME) business group at Moody's Analytics. He is responsible for developing and managing solutions for banks to improve their lending and credit decisioning to small businesses. He has been with Moody's Analytics for three years, and has been focused on SME strategy, analysis, and process for banking customers.

Nancy Michael
Senior Director, Product Strategy

Nancy works to conceive and build innovative solutions for credit assessment of small businesses. Drawing on her previous experience co-founding a small business, she has built products and strategies to help financial companies better serve the needs of their customers. Nancy previously led the Client Solutions team for the Training and Certification division and headed strategy and marketing for the company's training and consulting businesses.

Helene Page
Senior Director, Engagement Advisor

Helene advises on business requirements for Moody's Analytics credit assessment and origination products. She started her banking career in her native New Zealand with the Australia and New Zealand Banking Group. Since moving to London in 2012, she has worked as a credit partner for Santander Corporate Banking, and as part of the team launching crowd-funding platform Money&Co.

In a recent market research study focused on challenges of small business lending and credit risk assessment by banks, Moody's Analytics concluded that emerging technology, innovative use of data, and expectations of an enhanced borrower experience will drive significant change in small business lending in the coming years.

The study was based on interviews with traditional lenders and emerging players in the financial technology (fintech) space on how they segment their business customers, the processes they use to evaluate credit worthiness of small businesses, and the challenges with these processes. Findings from the interviews were complemented by secondary industry research; insights from participation in banking, fintech, and small business events; and ongoing engagement with Moody's Analytics customers.

The study had these objectives:

- Provide perspective on the current state of small business lending processes.
- Evaluate the trends affecting small business lending.
- Identify the challenges faced by banks and other financial institutions during the lending process.
- Assess the small business credit information market, including tools and solutions employed by lenders to evaluate the creditworthiness of their customers and prospects.
- Define a future state vision for efficient and profitable small business lending.

In this article, we provide a summary view of our findings based on this research.

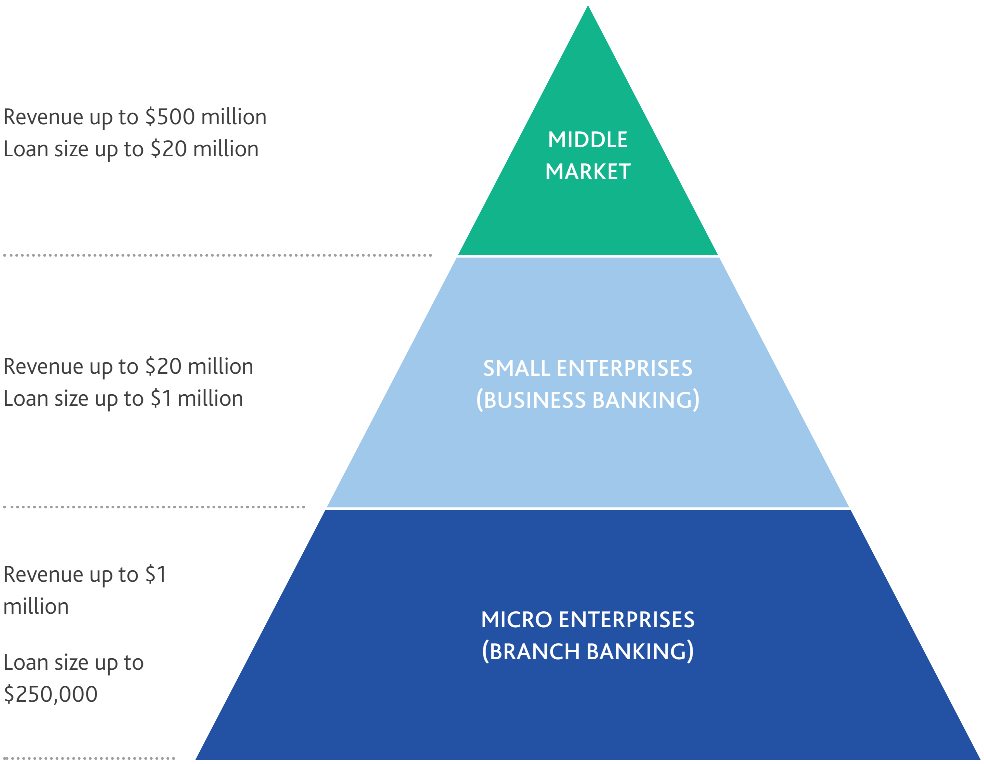
Overview of Small Business Lending

While the definitions of small and mid-sized business borrowers vary among financial institutions, these are the typical meanings:

- Micro enterprises are defined as businesses with less than $1 million in annual revenue, and loan sizes up to $250,000. These businesses are serviced primarily by the branch network.
- Small businesses are defined as those with approximately $20 million or less in revenue or $1 million or less in exposures. These businesses tend to be serviced by the business banking group.
- Middle-market organizations tend to be defined as those with aggregate loan exposure between $1 million and $20 million. They are typically serviced by the commercial banking or enterprise banking groups.

Figure 1 summarizes banks' definitions of businesses by size.

Figure 1 Bank definitions of small and medium-sized businesses



Source: Moody's Analytics

For small business lending above the branch banking level, most bank lenders request three years of financial statements, collected either via unaudited financial reports from the prospective borrower or in the form of tax returns for the business. Financials may be complemented with bureau data on credit utilization and payment behavior.

The collected data is typically applied in an internal scoring model with attributes assessing of external scores. Few banks have implemented auto-decisioning or indicated that they make small business loan decisions based primarily on a quantitative model. Figure 2 illustrates this process.

Challenges in Small Business Lending

Although small business loans constitute more than a quarter of the lending volume in the US, most banks do not have effective systems and practices to accurately and efficiently assess the creditworthiness of both the business and the proprietor or guarantors. This information is collected and entered manually into bank systems to produce an internal risk rating, which may be benchmarked against a number small business risk and seamlessly conduct lending activities. The challenges generally fall into two categories: data problems and process problems. With respect to data, these challenges exist:

> The small business lending process at most banks today is highly manual and conducted across a multitude of unintegrated systems. This results in a small business lending operation that is inefficient, inconsistent, and expensive.

» The credit information vendor market is fragmented, meaning financial providers and small businesses do not have a single source of credit information to meet their growing need for quality data.

» Banks use manual, time-consuming, and antiquated processes for collecting information from prospective borrowers.

» Once information is gathered, underwriters or credit managers spend significant time reconciling and merging data from various sources.

» Often, information on the credit risk of the owner or proprietor of a small business is used as a proxy for the risk of the business. Existing scoring models that are heavily weighted to consumer data lack credibility at levels above micro-businesses and generate high levels of manual overrides.

Even when lending decisions are made, a gap remains in terms of systems needed to document, monitor, and report on portfolio performance.

Banks may encounter challenges through every step of the lending cycle, from information-gathering through monitoring and portfolio management. These challenges are summarized in Figure 3.

Small businesses also face a unique set of challenges that make the process of getting credit difficult, including:

» Lack of knowledge of their credit risk and how they can improve their business credit standing.

» Opacity of banks' credit assessment process and expectations.

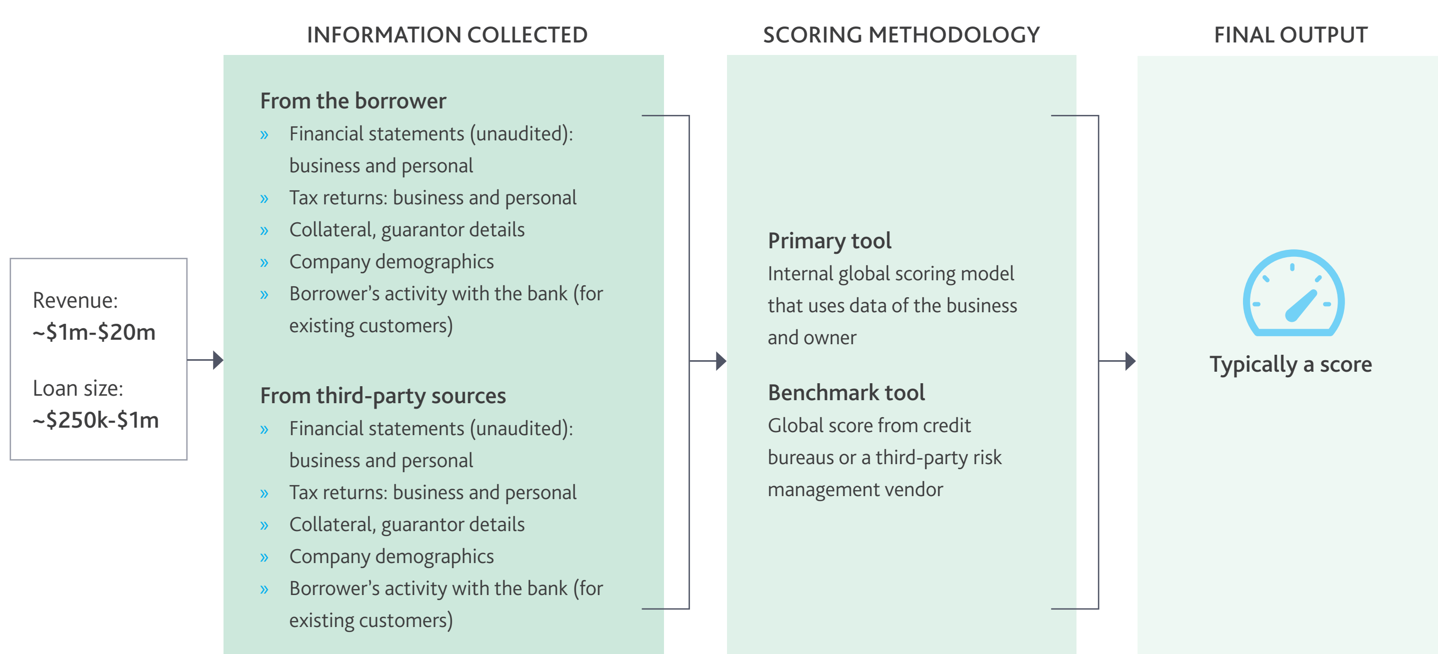
» Inconsistent requirements among banks in terms of the lending process, necessary data, and documentation.

» Difficulty in maintaining current and accurate financial reporting due to manual processes and lack of expertise.

Emerging Trends in Small Business Lending

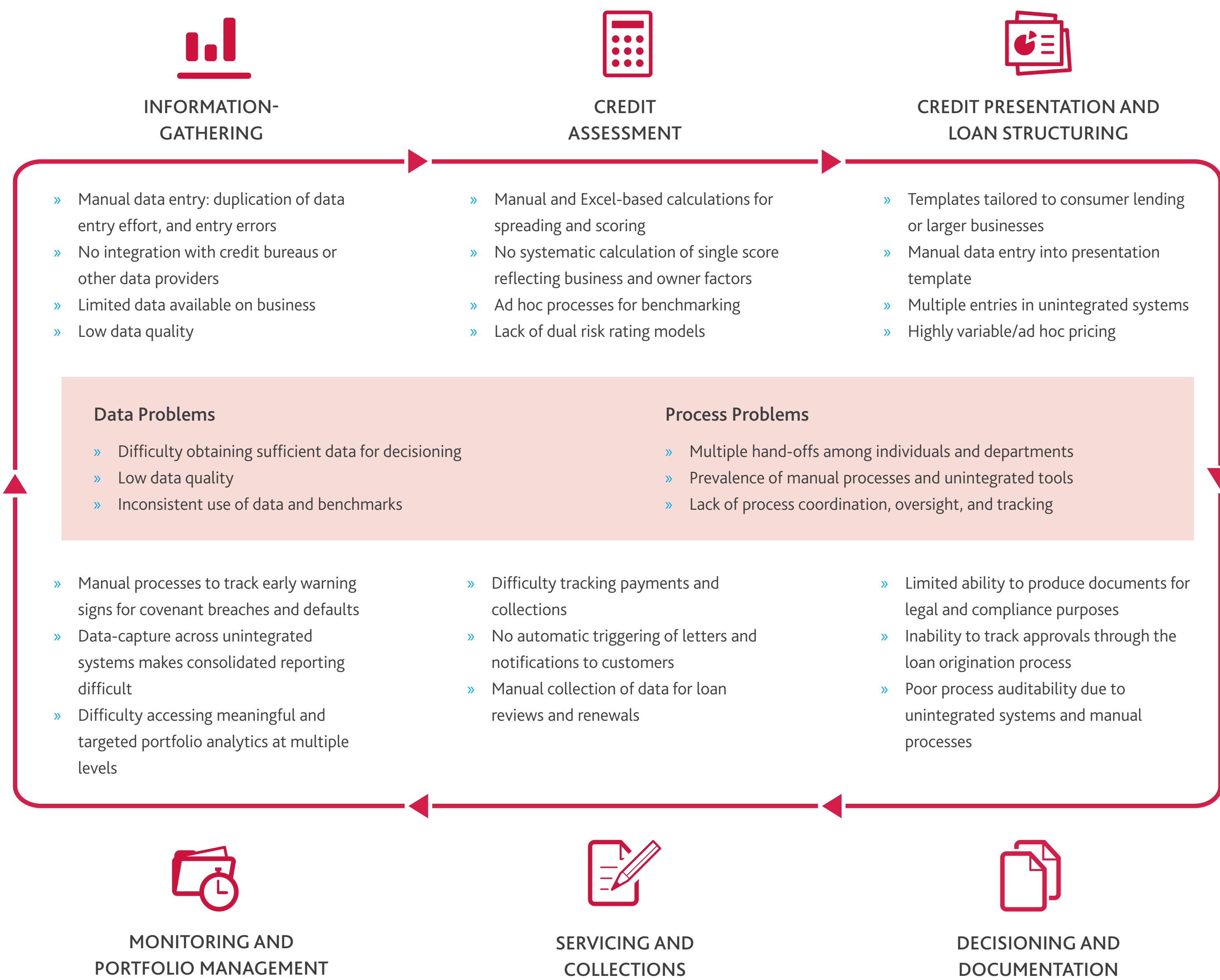
Small businesses are searching for easier access to loans in the face of shrinking funding and a lukewarm response from traditional banks, which

Figure 2 Small business credit assessment process in banks



Source: Moody's Analytics

Figure 3 Pain points faced by banks in the small business lending process



Source: Moody's Analytics

are struggling to buoy margins in a low interest rate regime. Alternative lenders are emerging at a feverish pace to fill this funding gap, but they have the challenge of creating reliable credit assessment models and bracing themselves for increased regulatory scrutiny. Against this background, we identified four categories of trends that will drive significant change in small business lending in the coming years (Figure 4).

Addressing the Challenges

Lending organizations have opportunities to improve the small business lending process in all parts of the credit life cycle. Organizations currently have these main opportunities for improvement:

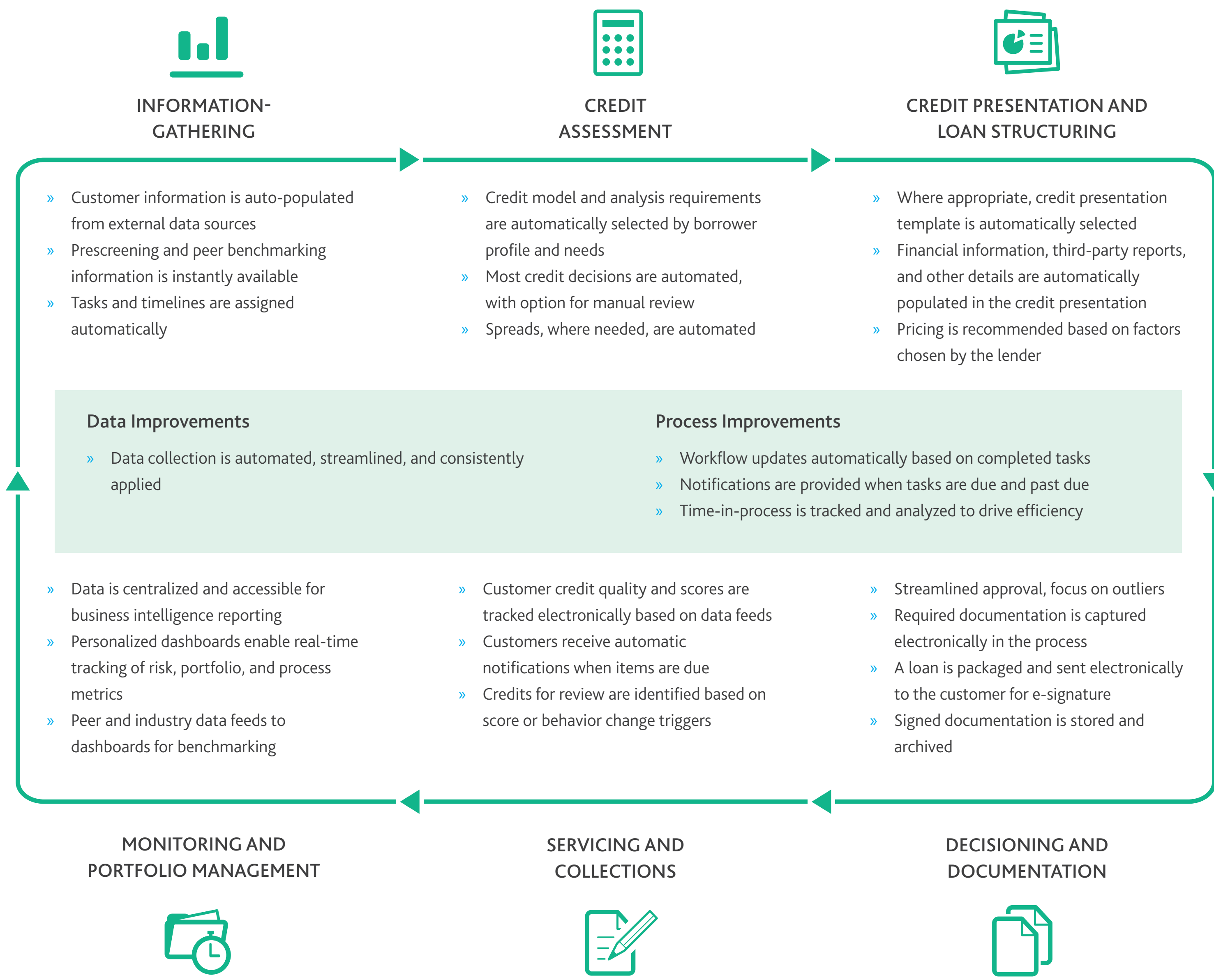
1. Streamline the collection of borrower information. Lenders commonly complain that small business information does not provide sufficient detail to make a lending decision. Borrowers argue that the information they produce is sufficient for them to run their business successfully, and that they do not have the resources to produce additional analysis. Banks can rethink the required information and more effectively differentiate the level of

Figure 4 Emerging trends in small business lending

Supply of Funding
» Large and mid-sized commercial banks will continue to drive the majority of small business lending, and they will continue to require more information from small businesses to make lending decisions. » Consolidation among smaller community banks will continue, contributing to a reduction in small business "relationship banking" and an increase in standardized processes and rules for small business lending. » There will be greater opportunities for small businesses to raise funds through alternate avenues (e.g., peer-to-peer firms, and insurance and asset managers) and capital markets (e.g., Euronext platform to invest in small and medium-sized enterprises). » As alternative lenders increase their credit volume, they are likely to be regulated more closely and require external models and tools to validate and improve their credit decisioning. » Lender margin pressures will continue as competition increases.
Demand for Funding
» Demand for small business funding is likely to increase as economic growth consolidates in the US and Europe. » Alternative lenders have expanded the population of the "bankable" beyond businesses and individuals with traditional scores. This trend is expected to continue as new data becomes available to evaluate credit risk. » The cost of funding for small businesses is likely to decrease as competition for loans to this segment intensifies. » Increased focus by government programs (e.g., the Small Business Administration) and small business-focused associations (e.g., the Small Business Financial Exchange) has led to more opportunities for funding.
Regulation
» Regulations are aiming to facilitate the entrance of new players in the small business lending space, while simultaneously addressing the risk to businesses and the economy posed by non-traditional models. » IFRS 9 will force lenders to shift some focus of risk management and capital allocation activities to earlier in the origination/decisioning process, and BCBS 239 will shift some focus to data management. » Stress testing regulations are a driver for financial institutions to build better models to quantify their risk more comprehensively.
Technology and Data
» Access to small business information will be critical. For micro businesses, transparency of the credit decision process and data requirements will be key. » Lenders will continue to aggressively expand the use of alternative types of small business information (e.g., big data) to evaluate risk, with the alternative lenders leading this space. » Fintech lenders have disrupted the small business lending process. Computerized lending decisions are leading to quicker loan decisions, less onerous security/guarantee requirements, and a dramatically enhanced customer experience. » Banks will adopt some of the practices of alternative lenders – such as increased automation of processes and reduced relationship banking – to remain competitive and maintain margins. Many will invest in fintech startups, contributing to a shake-out and consolidation of the highly competitive and rapidly evolving market. » The standards set by alternative lenders for a seamless experience, instantaneous decisioning, and process transparency will permanently change customer expectations of the experience with more traditional bank lenders.

Source: Moody's Analytics

Figure 5 The future state of small business lending



Source: Moody's Analytics

information requested based on the potential risk exposure. They can also explore new tools and data sources that facilitate data-gathering.

2. Leverage proven rating models for standard loans. Models are only as good as the quality and richness of the data that drives them. It is important to have proven and valid benchmarks based on a substantial and reliable dataset reflecting historical small business defaults. Individual lending institutions cannot – and should not – reinvent this wheel.

3. Update processes. The key issue here is the time it takes for a lender to process a loan application and disburse funds – the time-to-money. Banks should focus on automation of manual processes and implementing rule-based decisioning to fast-track simpler and lower-exposure loans and refocus precious resources on higher-value activities.

4. Upgrade infrastructure. Systems-related efforts should focus on removing duplicate tasks (e.g., multiple instances of keying in the same data) via integration and implementation of solutions with a lower overall cost of ownership. Outsourced or

cloud platforms can offer an attractive alternative since they typically do not require new hardware or additional IT staff, and they are automatically updated and backed up. Advanced software-as-a-service (SaaS) systems can provide a single, integrated solution for managing the entire credit life cycle.

5. Learn from the data. High-performing organizations will extract meaningful data to understand key performance indicators and meet audit and reporting requirements. Doing this effectively requires two things: first, a keen focus on exactly what data is the most meaningful; and second, data structures and systems that capture the right data and make it readily available for analysis. In addition, strict discipline and well-defined processes are necessary to ensure that the data is accurately captured and maintained.

The Path Forward: The Future State of Small Business Lending

Based on the findings of our research, including emerging trends and opportunities for improvement, the Moody's Analytics view of the future state of lending focuses on these elements:

- Tools to automate gathering and structuring of small business data from financial statements, tax returns, and other documents.
- Development of credit models using data and factors beyond financial information, and broader use of all data sources to optimize decisioning.
- Rule-based tools to automate processes and decisions, and workflow functionality to track tasks and requirements.
- Enhanced early warning, portfolio monitoring, and business intelligence capabilities.

Figure 5 shows how these aspects contribute to the future small business lending process.

To meet the challenges of a rapidly changing market, banks will need to adopt tools and technologies for enhanced data collection, process automation, automated scoring, and rule-based decisioning. Transforming the small business lending process will also require banks and their partners to leverage new credit information solutions and rethink the way they collect and use customer and prospect data to create credible, quantitative, and demonstrably validated credit decisioning frameworks.

Anju Govil contributed research to this article.

STRESS TESTING AND STRATEGIC PLANNING USING PEER ANALYSIS

By Dr. Anthony Hughes and Dr. Brian Poi

Banks face the difficult task of building hundreds of forecasting models that disentangle macroeconomic effects from bank-specific decisions. That is impossible when modelers rely solely on internal performance data and the standard set of macroeconomic variables released as part of the CCAR exercise. We propose an alternative approach based on consistently reported industry data that simplifies the modeler's task and at the same time increases forecast accuracy. Our approach is also useful for strategic planning as it allows one bank to compare its balance sheet and income statement to its peers and the industry and to explore potential mergers and acquisitions.

Dr. Anthony Hughes
Managing Director,
Economic Research

Tony oversees the Moody's Analytics credit analysis consulting projects for global lending institutions. An expert applied econometrician, he has helped develop approaches to stress testing and loss forecasting in retail, C&I, and CRE portfolios and recently introduced a methodology for stress testing a bank's deposit book. He received his PhD in econometrics from Monash University in Melbourne, Australia.

Dr. Brian Poi
Director, Economic Research

Brian is a director in the Specialized Modeling Group at Moody's Analytics, where he develops new products for forecasting and stress testing purposes and leads external model validation projects. He has a PhD and MA in economics from the University of Michigan.

Introduction

Responding to the dictates of the Dodd-Frank Act is, perhaps by regulatory design, a highly complex task for large financial institutions. In principle, banks must seek to carefully model every potential cash flow that may stem from the operation of their businesses. These models cover not only credit losses for all asset categories at a granular level – for many banks down to a loan level – but also asset and liability balances, loan origination volumes, deposits, interest and non-interest revenues and expenses, costs of staff and premises, and ultimately the exact future capital position of the institution.

In this article, we propose an alternative simple and coherent methodology that allows us to forecast and stress test the entire balance sheet and profit and loss statement for all of the roughly 6,000 banks in the US in a consistent manner. The output is presented as a bank-level panel database containing forecasts and stress scenarios for (potentially) every item covered by public call report data. We can currently project about 200 individual line items from the call report, with the potential to extend our methodology to more than 1,000 items.

Addressing Stress Test Limitations

Stress tests developed within banks have primarily utilized complex bottom-up modeling techniques. Analysts are tasked with building a model of a specific, narrowly defined cash flow or credit loss measure for the institution. They source data relevant to the line item, primarily from inside the bank, and then build a model that relates the collected data to macroeconomic variables. Once 1,000 modelers have built 1,000 models of 1,000 different variables, the series are projected and then combined to calculate the capital position of the bank under each scenario.

The complexity of this task has major implications for the banking system. First, even those institutions with the most keenly developed stress testing infrastructure cannot run an ad hoc stress test quickly and accurately. For example, suppose that a large, unexpected event – like the UK's vote to exit the European Union – occurs one weekend and the chief risk officer wants to determine its effect on the bank's future capital position. At present, it may take weeks or months for the manager to get the answer, by which time the next crisis, and the one after that, will have already come and gone. Ideally, bank executives should be able to conceive of a stress scenario during a morning coffee break, mull over detailed stress projections during a quick working lunch, and devise an appropriate strategy to deal with the potential threat by the close of business. One wonders whether a stress test that takes months to perform can ever have any meaningful strategic or tactical relevance to a bank of any size.

Ideally, bank executives should be able to conceive of a stress scenario during a morning coffee break, mull over detailed stress projections during a quick working lunch, and devise an appropriate strategy to deal with the potential threat by the close of business.

Another problem with the stress testing protocols, as currently implemented, is that banks often cannot compare their projected performance with that of their peers. With each bank building its own idiosyncratic, bottom-up model primarily based on internally sourced data, one bank's model outcomes may not easily compare with another's. This holds true even if the underlying portfolios face identical levels of risk. Banks can use an industry-wide model to calculate, say, default probabilities for a specific portfolio, but this will not account for changes in the mix of loans held by the bank or its rival institutions. In contrast, our approach is based on call report data, providing a consistent basis on which to compare banks across the size spectrum.

The fact that we can apply our method consistently for all US banks opens up a plethora of intriguing analytical options. For a specific bank, we can provide a coherent external projection of the complete financial position under baseline or stress circumstances. This can be used as a champion, challenger, or benchmark stress testing formulation to be compared with internal stress testing engines. Scenarios can be deployed within this framework in minutes, bringing the tactical stress testing protocol to a point that is well within reach.

Adding to the strategic possibilities, executives can lay their own bank's stress position alongside that of their competitors or potential collaborators. A bank considering an acquisition can fold the target's data into its own legacy data and make projections for the hypothetical merged bank. Banks can gain key insight into which of their competitors are more or less recession-prone than themselves, and can then potentially improve their recession resilience through acquisition. Additionally, a bank can determine whether its own internal managers are outperforming their peers in similar roles at competitor banks or whether they are merely riding industry waves.

Another intriguing element of this work is the breadth of banks that the analysis covers. We began this research to develop benchmarking options for the largest banks. We were pleasantly surprised to find that our methodology worked as effectively for small banks, even those with less than $1 billion in assets, as it did for Comprehensive Capital Analysis and Review (CCAR) giants. For banks in the Dodd-Frank Act Stress Test (DFAST) range – with $10 billion to $50 billion in assets – where available data often fail to deliver valid models, and where subjectivity plays an outsized and unwanted role in stress testing, our approach can be used to provide scientific rigor. For smaller community banks, our approach opens to them the stress testing floodgates. Insofar as larger banks are obtaining competitive benefit from stress testing, small banks will now be able to enjoy similar benefits.

For large banks, the methodology provides a useful, consistent benchmark for a variety of pre-provision net revenue calculations. Large bank executives will also be able to run quick stress tests for both themselves and their competitors, individually or jointly, and they can perform the analysis on potential merger and acquisition (M&A) targets. Mid-size banks may find the methodology suitable as a champion model. These banks have much smaller armies of modelers, and building models using only in-house data is often not practical. Many of the smallest banks do not have sufficient data for modeling, let alone any modelers to make use of those data, so they may benefit by having a source of quantitative, unbiased forecasts that can be compared to their competitors. Banks of all sizes can use our data for peer-group and market analysis.

Later in this paper we study a peer group of small banks to demonstrate our methodology. Specifically, we consider four banks that are all active in the central area of Texas: Extraco, First National Bank Texas, Central National Bank, and First National Bank of Central Texas. Assets for this group total about $8 billion.

Motivation

When developing a model for strategically analyzing bank portfolios, being able to distinguish between internal and external forces is critical. For example, suppose that during the housing boom of 2005 and 2006, your bank was making a concerted effort to increase its market share in the prime credit card sector. In analyzing portfolio originations and volumes, regressing observed volume on a range of economic variables will uncover a clear procyclicality; when the economy improves, loan origination growth tends to accelerate. The analyst must then try to identify whether it was the improving economy or the bank's aggressive marketing activity that was primarily responsible for the outcome. If the marketing strategy was effective, this would tend to falsely magnify the perceived effect of the business cycle on growth in the portfolio.

A model that does not explicitly account for internal actions cannot accurately forecast what will happen in a renewed stress scenario unless management is assumed to be inert and inflexible. For the models to have strategic applications, they must be capable of simulating a variety of management actions and the manner in which they interact with the external environment the bank faces.

Suppose we have two banks in separate universes, Good Bank and Bad Bank, both of which are subject to DFAST. They have similar overall risk profiles and both have made large loans to a hypothetical HWC Corporation, a maker of widgets. In 2008, a recession kicked off and HWC was in big trouble – there was a speculative boom in widgets, the bursting of which caused the recession, and HWC had massively over-invested in its Albuquerque operations. In both universes, the distribution of manager talent is the same, and industry commercial and industrial (C&I) losses in both realms rose to 6% as a result of the recession.

Both sets of bank managers tried various treatments to keep HWC afloat. The problem for Bad Bank's shareholders was that their managers were poorly skilled and, as a result, HWC failed; the bank therefore suffered deep losses. Good Bank's people, consummate professionals, offered HWC a timely refinancing package that staved off disaster for the company and for the bank. The recession was still tough on Good Bank's bottom line, whose C&I losses rose from 2% to 4%. Bad Bank also survived the subprime widget recession, albeit just barely. Its C&I losses soared from 2% to a whopping 12%.

While the distribution of management talent is the same in both universes, Bad Bank just happened to hire an inordinate proportion of bad managers before the last recession. The good managers were hired elsewhere.

After the recession, Bad Bank methodically fired its entire management team and rebranded itself as Satisfactory Bank.

Now DFAST rolls around again. Our friends at the rebranded SatBank are trying to build C&I models for use in the regulatory exercise. If they build a model of the internal data alone and seek to project under the severely adverse scenario, an event similar to the global widget crisis of 2008, they will project a 12% loss rate. The new CEO of SatBank is dissatisfied with this result, since she is certain that the new management team will do a better job than last time. Even if they hired a group of managers of average quality out of the available pool, they should at least be able to match the 6% result observed for the industry during the crisis.

Many of Good Bank's managers, meanwhile, have cashed in their options and are busy swinging in hammocks in warm places. The bank has restaffed from the same talent pool as SatBank. Can we not infer, therefore, that the two banks will now experience similar outcomes during a future severe recession?

It is possible to believe that Good Bank and SatBank will enjoy or endure similar results to those they experienced during the last recession. It would be more accurate, however, to assume that both banks will regress to the mean and behave more like the average bank going forward.

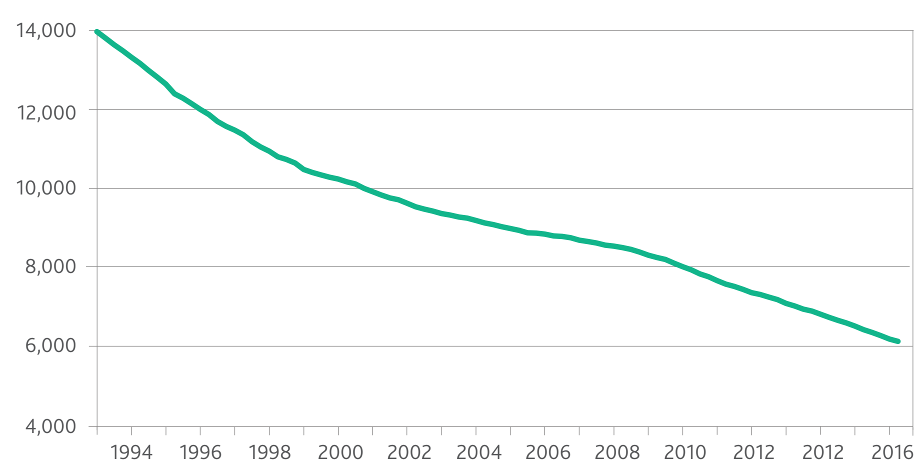
A conservative position, meanwhile, would involve assuming that both banks will err in their staffing choices. A tough but reasonable regulator may be justified in forcing Good Bank to capitalize to SatBank's numbers during its capital adequacy assessment. Moreover, even though Good Bank weathered the previous recession relatively well, it is not exempt from the need to benchmark to consistent external data. If the bank internalizes the view that it is recession-proof, that other banks' data do not pertain to it because it is above the fray, it is hard to see how the stress testing imperative has made the bank any safer.

How We Do It

Given the large number of banks in the US, we assume perfect competition so that exogenous actions taken by managers at an individual bank will not affect the trajectory of industry-level aggregates. Of course, decisions made by the large CCAR banks might in fact affect aggregate volumes, but for our purposes the assumption is especially powerful. It allows us to model the data on industry-level aggregate outcomes for each line item on the call report without worrying about the effect of any specific action taken by a manager at an individual bank. As Figure 1 shows, while the number of independent banks has been in steady decline, there are still 6,000 today, ensuring a high level of competition.

As a consequence of our assumption, we can model the behavior of the industry against cyclical economic variables and thus isolate the pure effect of the macroeconomy on the series of interest. This basic principle applies, to a greater or lesser extent, to all the series in the call report. Our assumption of perfect competition vastly simplifies our analysis by allowing us to

Figure 1 The number of banks in the US is in secular decline



Sources: FDIC Statistics on Depository Institutions, Moody's Analytics concentrate on pure macroeconomic factors and thus isolate the internal factors for analysis conducted separately.

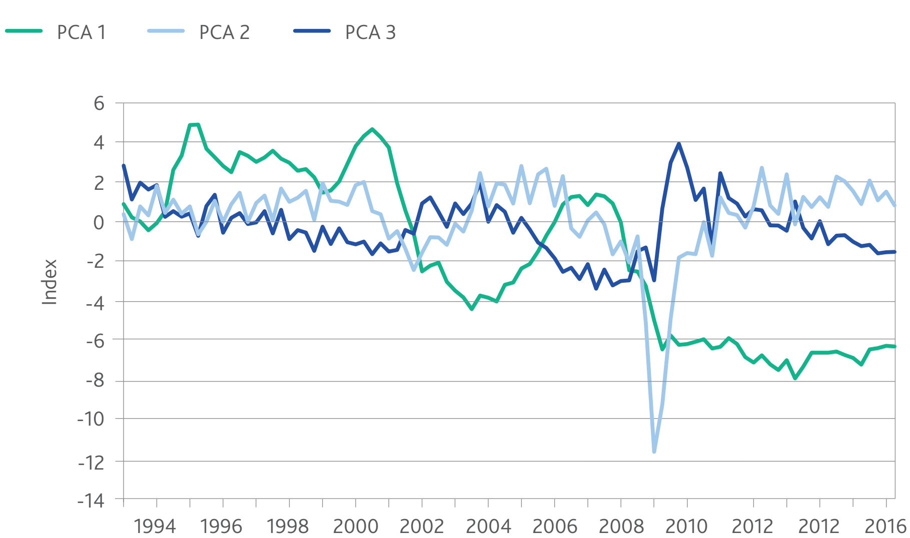
We model the aggregate series using standard macroeconometric techniques that are familiar to most readers. We also ensure that relevant identities hold. For example, our forecasts for total deposits reflect the sum of checking, savings, time, and other forms of deposits. We enforce consistency between the aggregate income statement and balance sheet by making interest income and expenses functions of assets and liabilities, respectively.

Before we can model an individual bank, we must adjust each existing bank's data for past M&A activity. For example, when Wells Fargo merged with Wachovia in 2009, the entity labeled "Wells Fargo" in the call reports almost doubled in scale from 2009Q4 to 2010Q1. We construct hypothetical data for Wells Fargo by combining Wells Fargo data with historical data for Wachovia and all other entities that have come under the Wells Fargo moniker over the years. Thus, our data for Wells Fargo represent what it would look like had it always owned Wachovia and the other banks it has acquired. Doing this allows us to control for what are perhaps the most obvious structural breaks in the data, those specifically due to M&A activity. Details of this approach are available on request.

Even after we adjust the bank-level data for M&A activity, some structural breaks will inevitably remain. Wells Fargo's managers clearly had different strategic goals than the Wachovia managers they replaced. If, say, Wachovia had a defensive manager in a specific area, replaced by a more aggressive post-merger overseer, we would see changes in the dynamic behavior of the relevant series after the merger. We use the database of bank M&A activity maintained by the Federal Reserve Bank of Chicago, a database which does not include acquisitions of non-bank entities. For example, if a bank acquires assets from an insurance company, our data will still show a spike in the bank's total assets and other series because our M&A adjustment algorithm does not account for that activity. Nevertheless, our adjustment handles the vast majority of M&A-related discontinuities seen in data.

With the merger-adjusted bank data in hand, we use the industry-level data and forecasts to produce our bank-specific forecasts. When the variable being modeled can take on negative values, as is usually the case with income and expense variables, we use a beta-model approach in which we model the bank-level variable as a function of the industry-level variable and macroeconomic factors. When the

Figure 2 Three principal components of the economy



Source: Moody's Analytics

variable being modeled can only take on positive values, as is usually true of assets and liabilities, we use a share-based approach in which we model the ratio of the bank-level variable to the industry-level variable as a function of macroeconomic factors.

Rather than attempt to find a small set of macroeconomic variables that can explain each of the 200 bank series we currently forecast, we instead use a principal components analysis (PCA) to identify a few uncorrelated latent variables that can account for the bulk of macroeconomic fluctuations. That is, we start with more than 100 macroeconomic and interest-rate variables and then run a PCA. The first three principal components can account for more than 85% of the total variance of all the macroeconomic variables. For small banks located within a particular state, we often replace the third PCA with a single PCA based on state-specific macroeconomic variables.

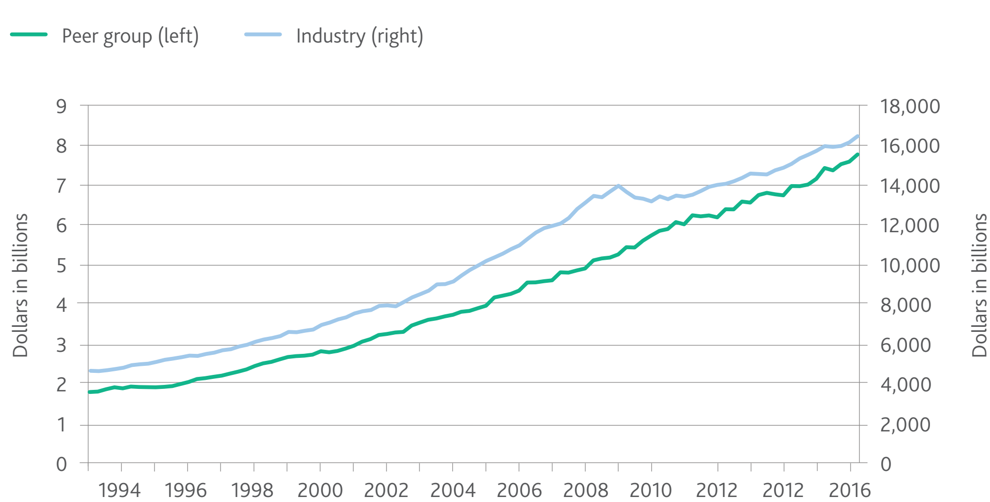
These principal components have intuitive interpretations. See Figure 2. The first principal component, PCA 1, closely follows long-term interest rates. Interest rates have been in secular decline since the early 1990s, but we have nonetheless experienced periods of rising rates. The second principal component reflects the cyclical behavior of the economy, falling during the recessions of 2001-2002 and 2008-2009 and bouncing back along with the economy. The third principal component is a lagging indicator of the economy; it peaked in 2004 and 2010, several quarters after the economy bottomed.

Whether we use the beta model or the share model to forecast an individual bank based on industry data, we use these same three principal components to control for economic conditions. We employ various combinations of lags of these three variables and then pick the model with the best forecast accuracy. Together with the scenario-specific forecasts of the PCAs and the industry-level bank data, we use the resulting model to forecast the individual bank.

The cyclical component of market share can be viewed as a measure of risk appetite. Suppose a particular bank has a rising market share in C&I loans during a period of strong growth for the C&I sector. Now compare this institution to one whose share of C&I volume rises during recessions. The bank that gains share during a recession is likely the more conservative bank. Conservative banks will lose market share to more aggressive competitors during upturns and then recover the lost share when competitors falter during tough times. In general, a bank with a high beta has a higher risk appetite. Approaching the problem in this way, we can measure the appetite for risk for all banks line-by-line across the entire call report.

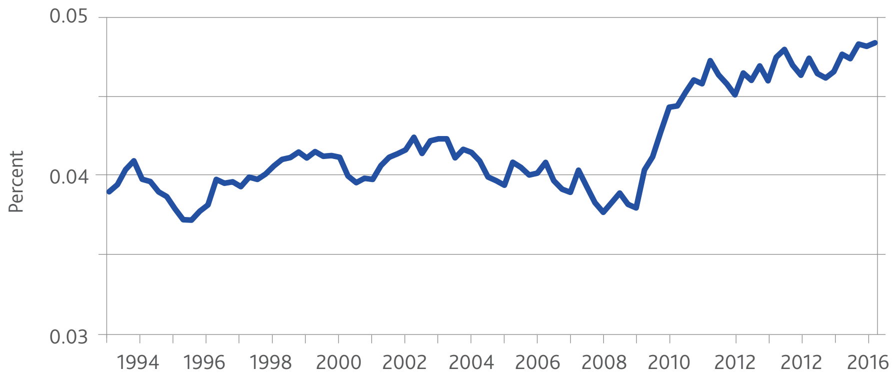
Regional economic conditions are most prominent among small banks. Figure 3 shows the total assets for a peer group of four banks located in central Texas as well as for the entire

Figure 3 Peer group and industry assets



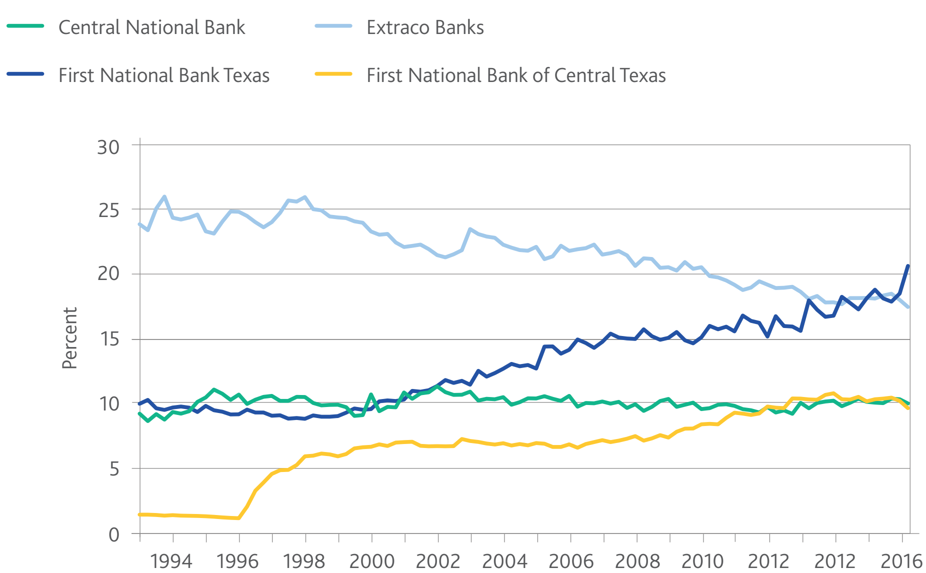
Sources: FDIC Statistics on Depository Institutions, Moody's Analytics

Figure 4 Peer group assets as a share of industry



Sources: FDIC Statistics on Depository Institutions, Moody's Analytics

Figure 5 First National Bank Texas gaining assets at Extraco's expense



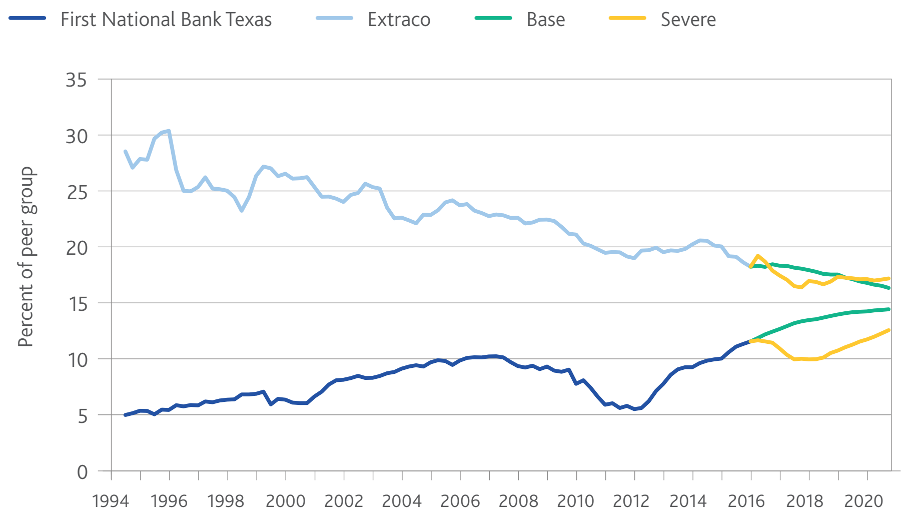
Sources: FDIC Statistics on Depository Institutions, Moody's Analytics

industry, and Figure 4 shows the peer group's assets as a share of industry assets. During the Great Recession, this peer group was able to increase its share from 0.038% to 0.047% during a nine-quarter period from 2008 to 2010. This increase was mainly due to banks in other parts of the country posting large declines in asset values. Including a component that controls for regional conditions helps us capture these effects. Interestingly, though, our four banks have been able to maintain (and even further increase) the share they achieved during the recession.

Changes in market share not attributable to national and regional economic factors are idiosyncratic in nature. An increase in market share can be achieved by taking greater risk, but it can also be achieved through more effective management. In either case, if the increase in market share cannot be attributed to the business cycle or regional variations, it can instead be chalked up to the good fortune and effectiveness of the bank's managers.

Figure 5 shows the market share for our four Texas banks, where we also included several smaller banks when defining the size of the

Figure 6 Net loan and lease share forecasts



Sources: FDIC Statistics on Depository Institutions, Moody's Analytics

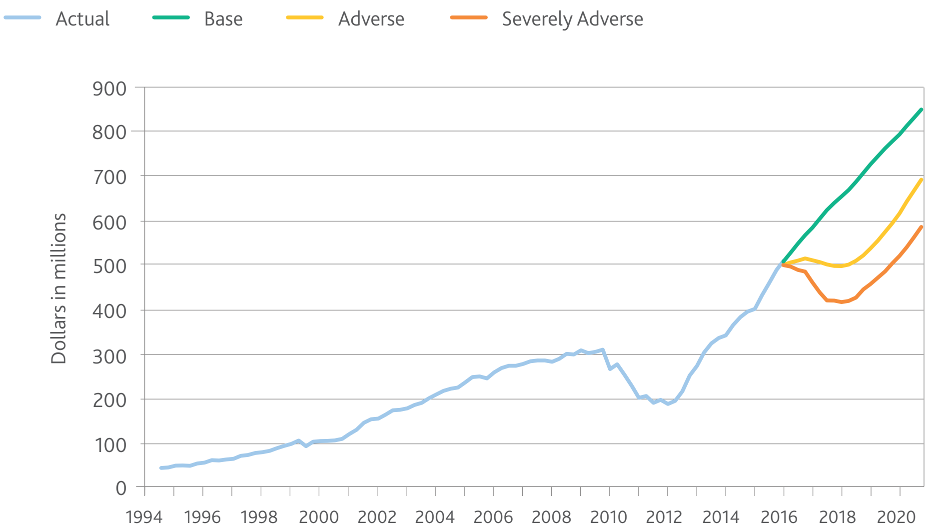
market. Extraco has clearly been losing market share over the past two decades. While Central's share has been steady, First National Bank Texas has seen its peer-group share rise consistently to the point where it has recently surpassed Extraco as the group leader in total assets. Having no data about the internal actions taken by any of the banks, we can nonetheless conclude that First National Bank Texas has been very effective in grabbing market share from its competitors. Extraco may well be pursuing a margin growth strategy and may be highly profitable for its shareholders, though there is no doubt that it is shrinking in scale relative to its fast-growing peer.

We have several options when forecasting market shares under baseline and stress scenarios. The simplest alternative is to assume a constant market share, either at its last historical value or perhaps its mean over a longer recent period. Even with this approach, our forecasts of the underlying bank-level variable of interest will still show different forecast trajectories because our industry-level forecasts do. A second alternative is to use an autoregressive integrated moving average (ARIMA) model to forecast market shares. This extends the flat-line approach by using recent market share momentum to help forecast the share going forward.

The third approach, as discussed previously, includes using PCA so that market share forecasts are conditional on the economic environment. When we fit these market share models (and beta models) using principal components as regressors, we do not place any restrictions on the signs of the corresponding parameters. Forming prior views of how these principal components affect a bank's market share is difficult. Is Extraco's (or Wells Fargo's) market share of commercial real estate loan origination pro- or counter-cyclical? In practice, that answer depends on the bank's strategic plan and tolerance for risk. We allow the data to speak for themselves in determining the dynamics of market share under different scenarios.

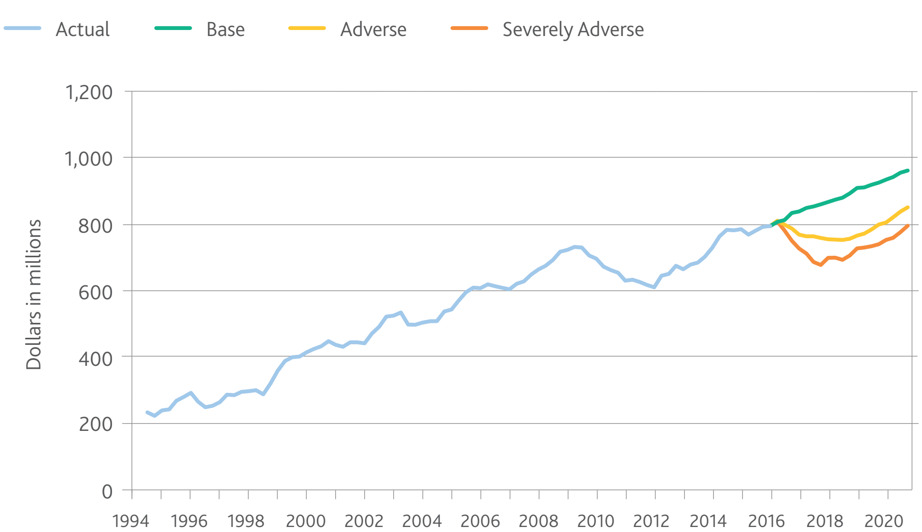
Figure 6 shows our forecast peer-group market shares of net loans and leases for First National Bank Texas and Extraco for the CCAR baseline and severely adverse scenarios. The behavior of Extraco's market share in the severely adverse scenario is interesting. It initially rises but then falls slightly. After 2017, its market share levels off, offering somewhat of a respite from the declines it has experienced for most of the past 20 years. In contrast, First National's market share growth comes to a halt before resuming in 2019 under the severely adverse scenario. Figures 7 and 8 show our forecasts for net loans

Figure 7 First National Bank Texas net loans and leases forecast



Sources: FDIC Statistics on Depository Institutions, Moody's Analytics

Figure 8 Extraco net loans and leases forecast



Sources: FDIC Statistics on Depository Institutions, Moody's Analytics

and leases under all three regulatory CCAR scenarios. Compare Figure 6 to Figure 8. In the baseline scenario, Extraco's market share continues to wane. Nevertheless, the industry grows enough so that Extraco's shrinking slice of the pie still translates to a growing loan and lease portfolio. In summary, for several line items in the call report, we have demonstrated that industry-level aggregate data are smooth and highly amenable to modeling against macroeconomic variables to produce stress scenarios. Further, we have demonstrated that the derived market share for individual banks (or a peer group of banks) is stable, demonstrating cyclical, regional, and idiosyncratic behavior. We have modeled such shares against principal components to extract the cyclical elements and thus isolated some key idiosyncratic behavior that is unique to the specific banks in our group. We have argued that measures of correlation between individual bank data and related industry-level data provide a valid measure of risk appetite that can be presented for each line item in the call report.

While the approach presented here is clearly top-down in nature, we note that the methodology allows us to dig down to any level of granularity required by end users. Had the alternative bottom-up approach been taken, and data for each bank were considered in turn, it would have been impossible for us to statistically separate the data into their collective and idiosyncratic components. We contend that it is only the collective components that should be stressed during a stress test and that a variety of idiosyncratic management responses should be considered as part of a strategic analysis used by the bank's managers to deal with stress.

Conclusion

Distinguishing between internal and external drivers is a problem of Gordian complexity. Stress testing, to date, has focused on individual banks building stress testing models based solely or primarily on internal data sources. It is unclear whether it is possible for a bank to understand all the risks it faces without looking for clues outside the castle walls.

There are various ways for banks to do this. One would involve producing detailed benchmark forecasts against which to peg internally derived solutions. There is, however, a distinct lack of suitable approaches that could be used to provide such a comparison. The methodology we present here represents arguably the first credible attempt to provide a universal benchmarking solution. We have used only externally sourced public data and have relied in no way on any information that is specific or proprietary to any individual bank. Despite this, we contend that the stressed and baseline projections produced would compete strongly with internally produced forecasts that rely on a detailed understanding of the inner workings of the bank.

The universality of our approach provides any number of benefits that are external to the core stress testing imperative. Managers of banks of all sizes can look at their own bank and competitor banks through the same lens. This means that strategic analysis can proceed via consideration both of action and competitor reaction to a variety of management plans. The external environment, meanwhile, is truly external in this approach. The stress scenario is therefore truly exogenous if considered in our framework.

Modelers who rely solely on internal data and macroeconomic variables cannot disentangle the effects of the macroeconomy on the one hand and bank-specific actions on the other. Our example of Good Bank and Bad Bank highlights the fact that a model that predicts credit losses in a stress scenario similar to those seen during the Great Recession is not conservative and is unlikely to be accurate. A rigorous stress test or strategic analysis requires the bank to compare itself to industry and peer-group aggregates.

We propose a novel, powerful modeling framework that uses FDIC call report data to develop both industry and bank-level forecasts. Aggregated call report data do not suffer from idiosyncratic management actions, so identifying the impacts of the macroeconomy becomes straightforward. Forecasting an individual bank then becomes a matter of explaining how its market share has evolved over time and how it is likely to behave under various economic scenarios. That task is much easier, and less error-prone, than trying to build a bottom-up model that tries to capture both macroeconomic effects and internal decisions.

BEYOND THE REGULATION: EXPLORING AN INNOVATIVE TOOL TO GAUGE COUNTERPARTY CREDIT RISK

By Dr. Samuel W. Malone and Ed Young

Opacity – rooted in fragmented markets, complex legal entity structures, and contingent liabilities – has prompted regulators to require more specific insight from certain financial firms into their interconnections. In this article, we highlight a new network-based toolkit that helps firms deal with associated regulatory requirements related to single-counterparty credit limits.

Introduction

In the first quarter of 2016, the Federal Reserve released a revised proposal that would establish credit limits for unaffiliated counterparties of large financial institutions.[1] The proposal – full of intricacies related to control relationships for economically interdependent counterparties – strives to provide additional transparency to the network of financial connections between large firms. Further details of the proposal are described in Figure 1.

While the proposed rule is a step toward improved financial market transparency, it has at least two weaknesses that require attention. First, it instructs financial firms to aggregate counterparties based on the likelihood that the distress of one could interrupt the other's payment of liabilities, but does not specify a clear way to assess such relationships. Second, a bank's ability to assess connections between two of its own counterparties does not necessarily allow it to detect problems arising from a third

Figure 1 Counterparty relationships

Affiliated counterparties outlined in the proposal are generally aligned with **control relationships**, following the Fed's definition of a subsidiary outlined in the Bank Holding Company Act of 1956.

The Fed's definition of **economically interdependent** counterparties is a bit more convoluted and is based on six criteria outlined in the proposal. Generally speaking, the criteria have been established to track counterparties that are likely to move in tandem due to various economic and legal relationships between the counterparties.

For the purposes of this article, we focus on the most open-ended of the six requirements: **financial distress spillover**. This is the likelihood that the financial distress of one counterparty will cause difficulties for another counterparty in terms of full and timely payment of liabilities.

Source: Federal Reserve

1 Board of Governors of the Federal Reserve System, 2016.

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counterparty linking these two.

We propose a tool that allows banks subject to single-counterparty credit limit (SCCL) rules to accomplish both of these objectives, and therefore to satisfy the SCCL requirements for economically interdependent counterparties in a more concrete manner.

SCCL Redux

If enacted in their current form, the new SCCL requirements will require large financial institutions in the US, both domestic and foreign, to track and report their net credit exposures to unaffiliated counterparties based on many specific criteria. As has been the case for many recent expectations from the Federal Reserve, the proposal tailors supervisory expectations based on the size of the firm as well as its systemic footprint. Limits for allowable exposures, as well as frequency of reporting, are tiered in a manner similar to the revised US Basel III capital rules.[2] Figure 2 outlines capital limits and reporting requirements for each tier of bank holding company (BHC).

The call for consistent data collection on a firm's large counterparties is appropriate. Without additional analytics, however, risk managers will not be able to take advantage of actionable risk information as a result of such efforts. By design, limiting the analysis to assessing direct, "one step" connections ignores a large majority of the credit risk pathways linking these large firms. We now describe briefly a network-based toolkit that solves this problem.

Counterparty Risk Identification with Dynamic Network Models

A bank's hedged and unhedged counterparty exposures provide direct measures for the potential for losses due to a counterparty default.

But indirect exposure, caused by the impacts of major counterparties on each other, can also play a significant role in raising a bank's credit risk. For this reason, banks must take counterparty contagion risk into account in the risk identification process. In particular, risk identification should capture the observed effects of counterparty probabilities of default (PD) on the bank's and other counterparties' PDs over recent history. This is a direct way of satisfying the "financial distress spillover" requirement of SCCL regulation discussed in Figure 1.

As a concrete illustration of these ideas, we present a short case study based on a large global bank. We use estimates of a dynamic network model[3] to measure the existence

Figure 2 SCCL capital and reporting requirements

Covered BHC Type (by Asset Size and Foreign Exposure)	Capital Requirement (Net Exposure)	Reporting Frequency
\$50 billion to \$250 billion in assets <\$10 billion in foreign exposure	<25% of total regulatory capital + ALLL	Quarterly
>\$250 billion in assets >\$10 billion in foreign exposure	<25% of Tier 1 capital	Daily
Major company (Global systematically important financial institution (SIFI))	<15% of Tier 1 capital (major counterparties) <25% of Tier 1 capital (other counterparties)	Daily

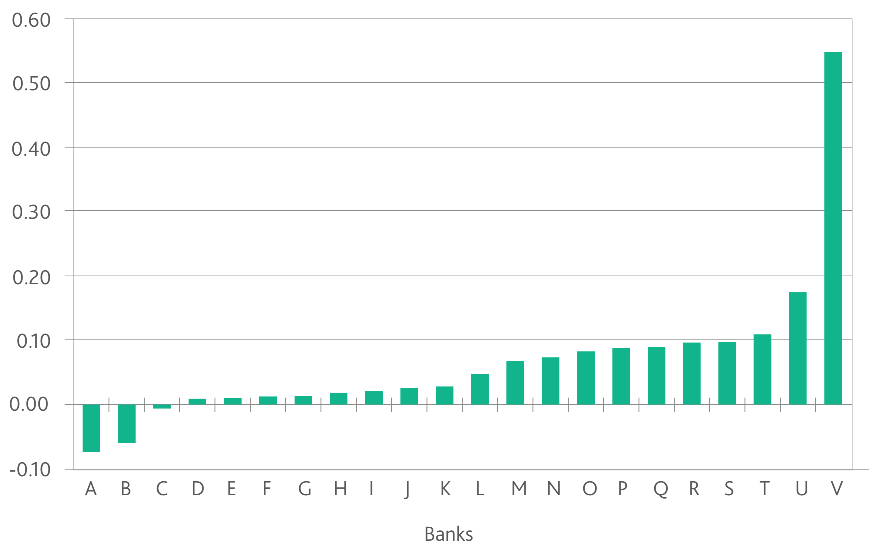
Source: Federal Reserve

2 Regulatory Capital Rules: Regulatory Capital, Implementation of Basel III, Capital Adequacy, Transition Provisions, Prompt Corrective Action, Standardized Approach for Risk weighted Assets, Market Discipline and Disclosure Requirements, Advanced Approaches Risk-Based Capital Rule, and Market Risk Capital Rule.

3 This is documented in Hughes and Malone (2015) and Malone (2015, 2016).

and strength of spillovers across counterparty PDs based on monthly data taken from the last five years. The underlying concept behind the dynamic network model is that of Granger causality. This is assessed based on the results of running a vector autoregression (VAR) using the PDs of each distinct pair of financial firms in information on firm balance sheets, the market value of traded equity, and a large history of observed default events. In the dynamic network methodology, firms whose EDF movements forecast movements in the EDFs of many other firms are recorded as being highly connected and having an outsized influence on systemic risk.

Figure 3 Strength of credit risk spillover for each direct counterparty bank



Source: Moody's Analytics CreditEdge

the network. The particular network we use for this analysis is the global megabanks network, which includes all publicly traded financial firms worldwide with at least $100 billion in assets on their books.

Analysis of a Case Study for a Large Global Bank

To illustrate the application of the network model to the "financial distress spillover" aggregation rule, we discuss briefly the case of an unnamed large global bank, which we will

> Counterparty risk analysis that ignores these secondary effects is likely to miss materially important channels for contagion of counterparty credit risk to a bank's PD.

The network model sources PD estimates from Moody's Analytics CreditEdge, which provides default probability estimates for publicly traded firms around the world. The specific metric it uses to measure a firm's PD is the one-year Expected Default Frequency (EDF™). EDF metrics are estimated using combined

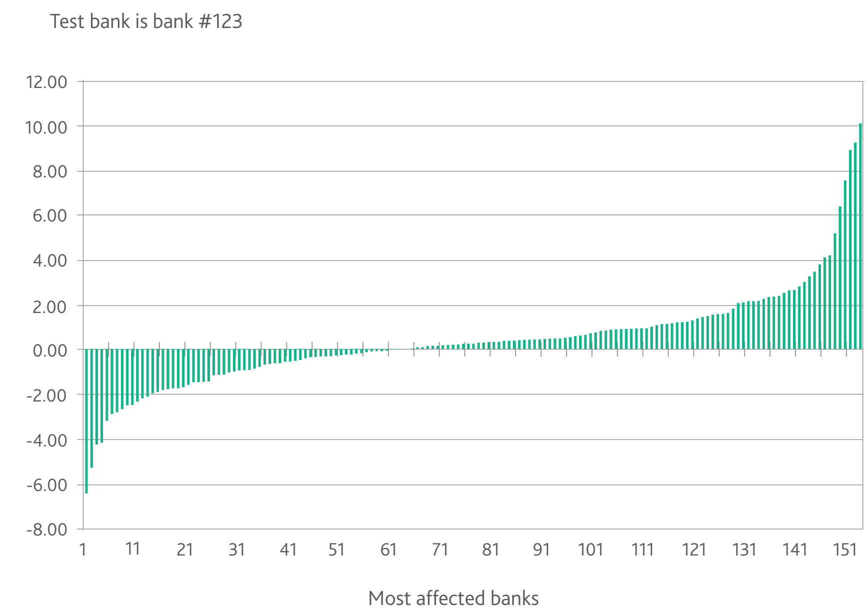
refer to as the "test bank." Note that the analysis that follows would proceed in exactly the same manner for any other bank in the network.

Our analysis relies on an anonymized list of 22 counterparties for the test bank, which was determined based on its largest direct counterparty exposures. Because we already know which counterparties the bank has direct exposure to, our interest is in comparing this information against the sensitivities measured by the dynamic network model and ranking the counterparties in order of the test bank's sensitivity to their PDs.

Our findings are as follows. First, of the 22 direct test bank counterparties, the measured predictive ability of one counterparty in particular – let us call this "counterparty V" – was much greater than for all the rest with respect to the EDF of the test bank. The sum of the first and second monthly lag coefficients in the VAR(2) models involving our test bank and each of its major counterparties, respectively, line up closely with the results of the F-test used to assess which banks Granger-cause the test bank's EDF. Figure 3 displays a bar chart of the values of these sums by (anonymized) counterparty, with counterparties arranged by increasing order of the sum. Somewhat surprisingly, we find that only bank V Granger-causes the test bank's PD (based on the 5% significance threshold for the relevant F-test), although the sum of coefficients is positive for all but three of the counterparties. By computing this same (or similar) measure for any bank in the network with respect to all of the other firms, it is straightforward to satisfy the Fed's "financial distress spillover" rule: Simply aggregate counterparties with positive spillover strength over an appropriate threshold.

Our second finding relates to validation. One simple way to validate the network model for the purposes of counterparty risk identification is to rank each of the financial institutions in the network based upon the combined strength that the credit risk of the test bank's 22 counterparties exerts upon them. If the test bank ranks highly in this list, this verifies that its list of major direct counterparty exposures strongly influences its credit risk. Upon performing this exercise for the network of global megabanks, we find that our test bank falls at the 80th percentile according to this measure for the list of 22 counterparties. This demonstrates that our test bank is high on the list of large financial firms whose credit risk is driven by the credit risk of its largest counterparties. Figure 4 illustrates this result.

Figure 4 Strength of counterparty group effect



Source: Moody's Analytics CreditEdge

Finally, on the issue of third-party risk transfer, much can be learned about potential knock-on effects from a counterparty default by looking at which of the test bank's counterparties Granger-cause each other and ranking which of these contagion channels are strongest.

When we do this exercise for the test bank, we find that all but one of its counterparties are Granger-caused by at least one other bank in its counterparty list. Further, of the 21 counterparty banks in the latter category, 18 are driven by at least two other counterparties. The strength of many of these relationships is quite high – even stronger than the effect of the test bank's most important counterparty on its own PD! Counterparty risk analysis that ignores these secondary effects is likely to miss materially important channels for contagion of counterparty credit risk to a bank's PD.

Conclusion

The systemic and counterparty risk surveillance tools provided by dynamic network models can be productively used to shed light on which of a bank's known counterparties most influence its credit risk based on measured relationships from recent history. Counterparties can be grouped based on the strength of their relationships with one another. Further information about the methodologies used here can be found in Hughes and Malone (2015) and Malone (2015, 2016). For regulatory purposes, the strength of the spillover effects between counterparties can be used to group them in order to satisfy SCCL regulation.

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INNOVATION ZONE

MAXIMIZING STRESS TESTING INVESTMENT: STRATEGIC CAPITAL ANALYSIS

By Joy Hart and Nihil Patel

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Joy has more than 10 years of financial services experience in a variety of areas. As a product management director, she currently focuses on development of portfolio risk management tools including RiskFrontier. Joy has a BS in aerospace engineering from Massachusetts Institute of Technology and an MBA from NYU Stern.

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Nihil is a senior director within the Enterprise Risk Services division at Moody's Analytics. He serves as the business lead driving our product strategy related to credit portfolio analytics. Nihil has broad experience in research, modeling, service delivery, and customer engagement. Prior to his current role, Nihil spent nine years in the Moody's research organization leading the Portfolio Modeling Services team as well as the Correlation Research team. Nihil holds an MSE in operations research and financial engineering from Princeton University and a BS in industrial engineering and operations research from UC Berkeley.

As new regulations require increased visibility of risk management processes, financial institutions often struggle to find strategic value in new investments beyond regulatory compliance. There is a need for tools that not only optimize long-term business strategy but also answer last-minute questions about rapidly changing economic conditions. Linking strategic tools with forecasting models can also provide greater clarity on the purpose of stress testing initiatives and therefore enhance regulatory compliance.

Financial Organizations Are Looking for Capital Strategy Management Tools

Regulatory requirements have increased across financial institutions in the past decade, and they continue to demand more transparency across the organization. While chasing regulatory compliance, senior management often lacks the time and resources to leverage the output of regulatory exercises for strategic insights. Firms have invested an estimated $12 billion to $15 billion in risk technology and data infrastructure, according to a McKinsey survey.[1] If they can appropriately leverage these investments, firms can expect benefits in the range of $19 billion to $24 billion. This paper focuses on how to unlock this value by using new tools to expand key performance metric forecasting under various economic conditions to guide and optimize business strategy.

There are a number of challenges and considerations that must be addressed to effectively forecast capital adequacy (e.g., Common Equity Tier 1). The scope of the calculation is the main issue, as the following must at a minimum be forecast consistently under each scenario:

» Charge-offs

» Allowances and resulting provisions

» Interest income and expenses, as well as other sources of income

» Risk-weighted assets

While all of these calculations are required for stress testing analysis, the key hurdle to leveraging stress testing infrastructure is the abundance of granular bottom-up models that are time-intensive and computationally demanding. However, understanding the portfolio and economic drivers in resulting forecasts remains critical and necessitates some drill-down abilities.

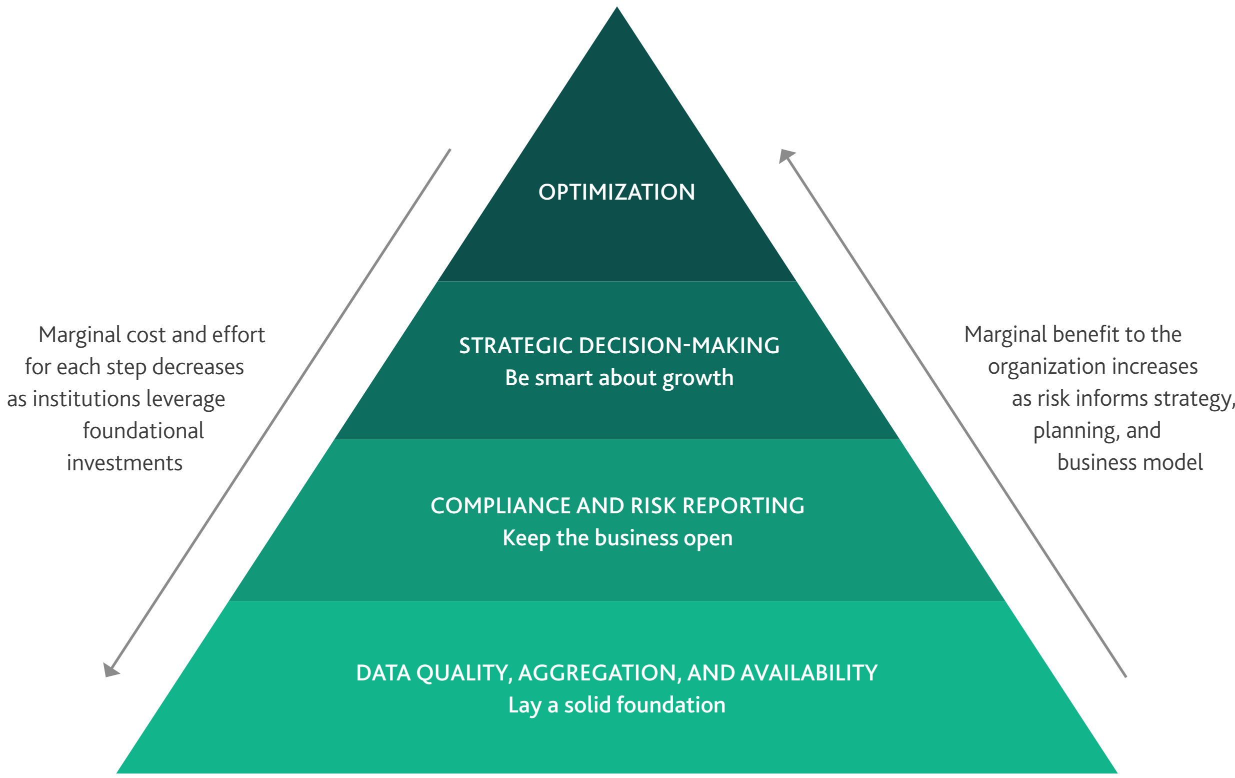
Currently, the processes in place for stress testing and other regulatory exercises focus on detailed granular analysis, but there is a market need for strategic tools to support a timely analysis for identifying which scenarios and strategies to drill into comprehensively. As shown in Figure 1, financial organizations have focused most of the investments on these goals:

» Data quality, aggregation, and availability

» Compliance and risk reporting

1 Harreis, Holger, Matthias Lange, Jorge Machado, Kayvaun Rowshankish, and David Schraa. "A marathon, not a sprint: Capturing value from BCBS 239 and beyond." *Risk.* McKinsey & Company. June 2015.

Figure 1 Financial institutions' main areas of investment



Source: Moody's Analytics

However, the $19 billion to $24 billion worth of benefits that McKinsey predicts are found in the top two layers:

- Strategic decision-making
- Optimization

When it comes to forecasting, capital planning groups are looking to understand the relative performance of scenarios, while regulators are continuing to ask how the organization ensures it adheres to its risk appetite. There is an increasing need for tools that optimize business strategy while simultaneously providing senior management rapid feedback on frequent "what if" scenarios.

A wide variety of "what if" market-moving events requires senior management to be adequately prepared by understanding the potential impact to their organizations. Events such as the UK's vote to withdraw from the EU and a Chinese growth slowdown have highlighted the need to consider and implement appropriate strategies for these events. Market sentiment shifts rapidly and many events happen overnight, causing senior management to request timely answers on the possible impact to capital forecasts. There is a clear need for an abbreviated top-down analysis to provide rapid feedback and assess many strategies prior to running a more thorough analysis on the chosen scenarios.

> One way to ensure consistency between strategic and regulatory initiatives is to directly anchor strategic results to forecasts generated by more granular models.

Moreover, regulators are increasingly focused on how financial institutions adhere to risk appetite statements. Ensuring that claims made to the market trickle down into actionable measurement at the business-line level has been a challenge across institutions. Management must also show regulators that their internal processes support a portfolio that will withstand a wide variety of economic conditions, which may require running quantitative analyses for those scenarios and considering multiple growth strategies that would perform well within risk appetite bounds.

Business strategy optimization is desired and often elusive for many financial institutions. Following the financial crisis, common practice has moved toward managing capital almost entirely based on the expanded regulatory requirements and standards, but buffers are necessary to account for unforeseen market conditions. Most organizations do not have a way to quantify the "right size" capital buffer, as they do not have an efficient way to analyze additional scenarios and strategic actions. Furthermore, as acquisitions continue and further complicate the equation, data is often not available to run detailed bottom-up models to project the impact on capital ratios.

Capital Strategy Should Link Directly to Business as Usual

Capital strategy decisions are heavily scrutinized by the market. Tools that can aid in business optimization and risk quantification will help link operations and processes across diverse financial institutions. Focusing on the drivers of capital metrics such as provisions, interest income, and expenses allows a communicable strategic vision.

Provisions are modeled through a combination of credit loss and allowance models, and they have significant impact on forecast capital ratios by directly impacting net income. Credit losses are highly correlated with the economic cycle, and they are critical for strategic and "what if" analyses. Risk management and allowance requirements often use granular loss modeling, while forecasts for new volumes can be at a more aggregated level.

Interest income and expenses, in conjunction with capital strategy, drive forecasts of capital expectations over time based on a given scenario. Tools developed need to have flexibility in assumptions around items that contribute to net income.

Strategic tools should be tied directly to other models used by various business lines in financial institutions. One way to ensure consistency between strategic and regulatory initiatives is to directly anchor strategic results to forecasts generated by more granular models. The anchoring ensures strategic tools can produce directional indication for additional "what if" analyses and business strategies under consideration.

In conclusion, many financial institutions would benefit from using strategic decision-making tools that offer timely ways to consider strategies and manage risk appetite from the top down. In the past, capital planning, risk management, and portfolio management remained in silos within organizations, and in many cases, those functions were further distributed by region. Increasing scrutiny by the market and regulators has led to increasing demands on senior management to quantify and be able to justify strategic actions and decisions. This, in turn, has been driving the demand for tools that can be leveraged for strategic decision-making and optimization.

REGULATORY REVIEW

ARE INTERNAL CREDIT MODELS FOR STRUCTURED SECURITIES GOING AWAY? AN ANALYSIS OF THE RECENT BASEL CONSULTATIVE DOCUMENT

By Richard Peterson

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There has been a lot of news analysis regarding the Basel Committee's direction to revert back to standardized approaches to assess risk-weighted assets, including constraints on the use of internal model approaches when assessing structured securities within the credit risk capital framework. While the impacts of this proposal may change the way internal models are formulated and utilized by banking institutions in structured securities analysis, we do not believe they will be abandoned anytime soon. The article focuses on the proposed changes and their implications for calculating credit risk capital, as well as the proposal's integration with Basel's other recent revisions and upcoming initiatives. The article also discusses what next steps are expected with regard to this proposal.

The Basel Committee on Banking Supervision (BCBS) published a consultative document on March 24, 2016 titled, "Reducing variation in credit risk-weighted assets – constraints on the use of internal model approaches."[1] This reduced reliance on internal models is consistent with the language expressed or implied in other recent publications such as the recently finalized fundamental review of the trading book[2] and the recent amendment to the Basel III securitization framework.[3] The proposed changes are intended to reduce the complexity of the credit risk regulatory capital framework, bring internal models in line with market risk proposals, and address jurisdictional differences in their calculations. The proposed changes are not specifically intended to increase capital requirements; however, that seems to be an effect.

How Did We Get Here? It's Complicated

Per the Basel III final rule, all banks are subject to the standardized approach (SA) to calculating capital. This approach allows capital to be calculated with a minimal number of inputs derived from a bond's current credit enhancement, serious delinquencies, and external ratings where approved. This, however, introduced major differences in the calculation based solely on a bank's jurisdiction. It has either been adopted using the simplified supervisory formula approach (SSFA), which is utilized in the United States, or the external ratings-based approach (ERBA), primarily used in Europe. The same bond can have a very different risk weight result depending on where it is calculated.

The Basel Committee aimed to level the playing field by issuing a revision in July 2016 to the Basel III securitization framework which also

1 Basel Committee on Banking Supervision. "Reducing variation in credit risk-weighted assets – constraints on the use of internal model approaches." BCBS D362. March 2016.

2 Basel Committee on Banking Supervision. "Minimum capital requirements for market risk." BCBS D352. January 2016.

3 Basel Committee on Banking Supervision. "Revisions to the securitisation framework." BCBS D374. July 2016.

incorporates an alternative capital treatment for simple, transparent, and comparable (STC) transactions. The European Commission went a step further, developing similar but slightly more exhaustive criteria for securitizations considered simple, transparent, and standardized (STS).[4] Both frameworks help bolster the securitization market as a viable funding source, bringing it more in line with covered bonds which have benefited from more preferable capital treatment. It is expected that the criteria within the STS and STC standards will standardize going forward.

The goal of the revised framework is to incentivize transparency and simplicity in structures, while also reducing the potential for regulatory arbitrage globally. The new approach presents a variation on the current standardized approaches that is more conservative than the current formulas for non-STC and non-senior tranches. STC tranches would, however, benefit from a lower potential capital floor (10% for senior tranches and 15% for non-senior tranches).

While all banks are subject to the standardized approach, some banks, based on an asset-based test, are also subject to the advanced approach per Basel III. For banks that qualify, an advanced model is an internal ratings-based model developed using the advanced approach for calculating capital. Capital is calculated using a number of inputs including probability of default (PD) and loss given default (LGD). The recent amendment to the Basel III framework also incorporates rewarding STC transactions that are subject to the advanced approach.

Advanced models are thought to be difficult to develop and support, and they are perceived as less transparent or easy to regulate. Critics contend that one can "game" the system with a model that is difficult to understand, quantify, and regulate by a governing body that was not involved in its creation. This perceived lack of transparency has spooked regulators, leading them to signal to the market that they intend to severely limit or even phase out the use of advanced models altogether.

To better understand the differences, see Figure 1 for a comparison of the current hierarchy with the newly amended hierarchy among advanced banks by jurisdiction. Figure 2 is an approximation of what three asset-backed security (ABS) bonds might look like under the new Basel III standardized approach with STC.

Where Do We Go From Here?

The BCBS is heavily pushing acceptance of its revised standardized approaches for both market risk and credit risk, irrespective (and perhaps because) of the forecast increases in capital. It is now coupling that with the proposed constraints on the use of advanced models, and it seems to be trying to temper the increases in capital with less punitive calculations for transactions deemed STC/STS. While this all seems very reactionary to the current regulatory and political environment, we believe advanced models will always have a place in advanced banks, as their benefits far outweigh the hurdles necessary to create, validate, and maintain them.

With the introduction of the amended Basel III rule, the standardized approach for non-STC transactions will effectively force banks to exit some lines of business that will no longer be profitable. However, an advanced model may allow for a more favorable capital result and thus a "stay of execution" for certain businesses. In addition, advanced models provide needed insight into the underlying collateral pools, and they forecast risk and sensitivities much better than a standardized formula ever could, no matter how much banks tweak it. The intelligence gleaned from an advanced model is not just used for regulatory capital, but also for internal profitability metrics and analytics, as well as resource allocation decisions.

Now let's turn to the regulatory capital impacts. Figure 3 shows a recent Pillar 3 disclosure published by JPMorgan Chase. The Pillar 3 disclosure is meant to enable the market to gauge the capital adequacy of an institution by providing details on the scope of risk exposures and giving further insight into the internal management of risk. Figure 4 summarizes the differences in approaches from Figure 3 in the

4 European Commission. "An EU framework for simple, transparent and standardised securitization." February 18, 2015.

Figure 1 Current hierarchy versus amended hierarchy for Basel III by jurisdiction

United States		Europe		
Current Hierarchy	Proposed Hierarchy	Current Hierarchy	Proposed Hierarchy	
Advanced model (SFA)	Advanced model (stricter requirements for approval)	Advanced model (IRB)	Advanced model (stricter requirements for approval)	If the bank has an approved internal ratings-based (IRB) model, it must use that model to compute capital. In the US, this is called the supervisory formula approach (SFA). Under the new hierarchy (and per the BCBS consultative document), the advanced model will be much more difficult and burdensome to get approved.
Standardized formula (SSFA)	Revised standardized formula (more punitive than current SSFA)	Standardized formula (ERBA or SEC-SA)	Revised standardized formula (more punitive than current ERBA or SEC-SA)	If no IRB model is available, depending on jurisdiction, a bank will use a standardized formula to compute capital. This is the simplified supervisory formula approach (SSFA, equivalent to SEC-SA in Europe), or the ERBA. Under the amended hierarchy, the new standardized formula is similar to current SSFA and SEC-SA, but is much more punitive than the current calculation for non-STC transactions.
1,250%	1,250%	1,250%	1,250%	If the bank does not have enough information to calculate via SSFA, ERBA, or SEC-SA, then it must assign the most punitive risk weight, 1,250%, to the position. This is not set to change.

Source: Moody's Analytics

20-50% bucket. It is in these risk weight buckets, non-senior middle-of-the-capital-stack tranches, where advanced models typically make the most impact.

Coincidentally, in this example, the difference in calculated securitization exposure between SFA and SSFA was only $2 million. However, the blended risk weight difference was almost 9 percentage points between advanced and standardized approaches. This difference meant an additional $337 million, a 38% increase in risk-weighted assets (RWA) over the advanced approach. This illustrates how a relatively small difference in calculated risk weight (9 points) can have a major impact (a $337 million increase in capital) at a large global bank. The resulting increase in RWA from the standardized approach, even in its current form, would prompt bank management to consider shifting focus to more profitable lines of business, potentially cutting off origination and support business on a number of asset classes.

What's Next?

In closing, so long as there is a mandate or even an option, we believe there will always be a strong incentive for advanced banks to develop and utilize an advanced model. The industry reaction to the BCBS consultative document has been swift and unsurprisingly unfavorable. The Institute of International Finance, an industry lobbying group representing most major industry players, issued a response letter on June 3, 2016 detailing how "reducing the alignment of capital and risk could negatively and unnecessarily affect the availability and pricing of credit to the economy." [5]

As you might expect, if implemented as drafted, the proposal will have major impacts on the types of financial products available. It seems simple: It is counterintuitive to the BCBS's goals to remove a bank's incentive to develop and maintain advanced models that attempt to adequately and thoughtfully assess risk profiles. Trying to encapsulate everything in a one-size-

5 Portilla, Andrés. "Re: Consultative Document, Reducing variation in credit risk-weighted assets – constraints on the use of internal model approaches." Institute of International Finance. June 3, 2016.

Figure 2 Indicative bond risk weight comparison

Asset Type	Tranche	Current Risk Weight, US*	New Risk Weight**	Difference (Percentage Points)	Comments
Auto, STC/STS	A1	20%	10%	-10	New floor of 10% for STC/STS senior tranches
	A2A	20%	15%	-5	
	A2B	20%	15%	-5	
	A3	20%	15%	-5	
	A4	20%	15%	-5	
	B	632%	884%	252	Mezzanine tranches are particularly impacted
	C	1,106%	1,174%	68	
Residential Mortgage-Backed Security (RMBS) (Jumbo 2.0)	A1	20%	48%	28	~1.5x increase in capital
	B1	1,250%	1,250%	0	
	B2	1,250%	1,250%	0	
	B3	1,250%	1,250%	0	
	B4	1,250%	1,250%	0	
	B5	1,250%	1,250%	0	
Commercial Mortgage-Backed Security (CMBS)	A1	20%	20%	0	
	A2	20%	20%	0	
	A3	20%	20%	0	
	AS	20%	111%	91	More than 5x increase in capital; an internal model would likely revert the risk weight back to 20%
	B	62%	267%	205	Mezzanine tranches are particularly impacted
	C	277%	580%	303	Mezzanine tranches are particularly impacted
	D	820%	1,001%	181	Mezzanine tranches are particularly impacted
	E	1,250%	1,250%	0	
	F	1,250%	1,250%	0	
	NR	1,250%	1,250%	0	

*The risk weights presented are based on the current Basel III rules in the US. Other jurisdictions may vary.
** The amended Basel framework is set take effect in January 2018. However, it is not yet clear whether or how the US or other local regulatory agencies will adopt it.

Source: Moody's Analytics

Figure 3 Pillar 3 disclosure

	Securitization							
	SFA		SSFA		1,250%		Total	
March 31, 2016 (in millions)	Exposure	RWA	Exposure	RWA	Exposure	RWA	Exposure	RWA
Risk weight								
= 0% ≤ 20%	$ 60,588	$ 12,804	$ 68,594	$ 14,420	—	—	$ 129,182	$ 27,224
> 20% ≤ 50%	3,787	876	3,785	1,213	—	—	7,572	2,089
> 50% ≤ 100%	157	119	842	701	—	—	999	820
> 100% < 1,250%	26	111	706	1,838	—	—	732	1,949
= 1,250%	7	81	80	1,017	397	5,248	484	6,346
Securitization, excluding re-securitization	$ 64,565	$ 13,991	$ 74,007	$ 19,189	$ 397	$ 5,248	$ 138,969	$ 38,428

Source: JPMorgan Chase

Figure 4 JPMorgan Chase methodology comparison (20-50% bucket)

	SFA	SSFA	Difference
Exposure (millions)	$3,787	$3,785	$2
Blended Risk Weight	23.1%	32.0%	8.9 points
RWA (millions)	$876	$1,213	$337

Source: JPMorgan Chase

fits-all standardized approach, now with many more layers and carve-outs for STC transactions, would not level the playing field; rather, it would create another distortion and likely lead to structural changes in the market and the shrinking of certain asset classes. In many cases mezzanine tranches would be overstated when using the new standardized approach due to its much more punitive calculation (as illustrated in Figure 2). Riskier assets may see the opposite effect, as more granular loan information will not be utilized and the new standardized approach may give a less conservative answer.

> The intelligence gleaned from an advanced model is not just used for regulatory capital, but also for internal profitability metrics and analytics, as well as resource allocation decisions.

As such, there may well be incentives for banks to move toward riskier assets to make up for the additional charges, the opposite of the BCBS's intent. Without a doubt, there will be a shift internally at all banks to optimize their risk and profitability at the desk level, and some origination businesses will be heavily constrained or even shut down. In order to maintain current levels of profitability, advanced banks will need to go through whatever hoops are necessary to have IRB models approved. Don't expect them to go away anytime soon.

BASEL III STANDARDIZED APPROACH TO COUNTERPARTY CREDIT RISK (SA-CCR): ADOPTION AND IMPLEMENTATION STATUS

By Jonathan Séror

More than two years after its publication by the Basel Committee, and a few months before its scheduled adoption, the new standardized approach for measuring counterparty credit risk is still in the process of being implemented. This article provides a brief introduction to this method, its expected benefits, and its actual impacts. It also details the potential difficulties associated with its implementation and the current status of its adoption in member countries.

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The standardized approach for counterparty credit risk (SA-CCR) is a new computational method for exposure at default (EAD) under the Basel capital adequacy framework. It is due to replace both the current exposure method (CEM) and the standardized method (SM) starting January 1, 2017. Introduced by the Basel Committee for Banking Supervision (BCBS) in September 2013, it aims to address weaknesses in margining recognition, sensitivity, simplicity, and uniformity across national authorities.

This is the new SA-CCR formula for computing EAD:[1]

exposure at default = alpha x (replacement cost + potential future exposure)

Key Changes and Impacts

SA-CCR inherits the 1.4 alpha factor from the Internal Model Method (IMM), used to obtain a loan-equivalent exposure conversion. Note that national supervisors may use their discretion to require a higher alpha based on a firm's counterparty credit risk exposures. Furthermore, banks may seek approval from their supervisors to use internal estimates of alpha, subject to a floor of 1.2.

It also differentiates margined and unmargined cases, in the computation of both replacement cost (RC) and potential future exposure (PFE). RC is an estimate of the amount a bank would lose if the counterparty were to default immediately, while PFE reflects increases in exposure that could occur over time. PFE is the asset-class-specific product of a multiplier and an add-on. The new formulas allow for a better recognition of collateralization, as well as offsetting benefits.

SA-CCR supervisory factors and single-systematic-factor correlations have been thoroughly calibrated based on four exercises. The new add-on percentages are more conservative for equities and commodities, as shown in Figure 1.

Implementation Challenges

Successful implementation requires a full understanding of the hedging set concept and of the margining processing under SA-CCR. The computation of the PFE add-on component is the most complex, as it varies widely depending on the asset class and subclass, collateralization, margin set, and netting set considered.

Identifying, sourcing, and arranging all the input

1 BCBS, April 2016.

Figure 1 Comparison table between CEM and SA-CCR supervisory weighting factors

<table>
<tr><th rowspan="3">Asset Class</th><th rowspan="3">Subclass</th><th colspan="4">Add-On Computation: Supervisory Weighting Factors</th></tr>
<tr><th rowspan="2">SA-CCR</th><th colspan="3">CEM</th></tr>
<tr><th>Maturity of 1 year or less</th><th>Maturity of 1-5 years</th><th>Maturity greater than 5 years</th></tr>
<tr><td colspan="2">Interest rate</td><td>0.50%</td><td>0.00%</td><td>0.50%</td><td>1.50%</td></tr>
<tr><td colspan="2">Foreign exchange (FX)</td><td>4.00%</td><td>1.00%</td><td>5.00%</td><td>7.50%</td></tr>
<tr><td colspan="2">Equity, single name</td><td>32.00%</td><td rowspan="2">6.00%</td><td rowspan="2">8.00%</td><td rowspan="2">10.00%</td></tr>
<tr><td colspan="2">Equity, index</td><td>20.00%</td></tr>
<tr><td rowspan="2">Commodity</td><td>Electricity</td><td>40.00%</td><td rowspan="2">10.00%</td><td rowspan="2">12.00%</td><td rowspan="2">15.00%</td></tr>
<tr><td>Other</td><td>18.00%</td></tr>
<tr><td rowspan="7">Credit, single name</td><td>AAA</td><td rowspan="2">0.38%</td><td colspan="3" rowspan="4">5.00%</td></tr>
<tr><td>AA</td></tr>
<tr><td>A</td><td>0.42%</td></tr>
<tr><td>BBB</td><td>0.54%</td></tr>
<tr><td>BB</td><td>1.06%</td><td colspan="3" rowspan="3">10.00%</td></tr>
<tr><td>B</td><td>1.60%</td></tr>
<tr><td>CCC</td><td>6.00%</td></tr>
<tr><td rowspan="2">Credit, index</td><td>IG</td><td>0.38%</td><td colspan="3">5.00%</td></tr>
<tr><td>SG</td><td>1.06%</td><td colspan="3">10.00%</td></tr>
</table>

Source: BCBS

data required for these calculations presents another challenge. Ensuring that the results obtained running SA-CCR match the expected figures from a theoretical standpoint is equally tricky. Moreover, it is important to verify that the exposure differences observed with the use of CEM and SM methods are accurate.

What Our Clients Are Saying

We asked some of our client banks about their perspectives on SA-CCR. Their feedback is as follows:

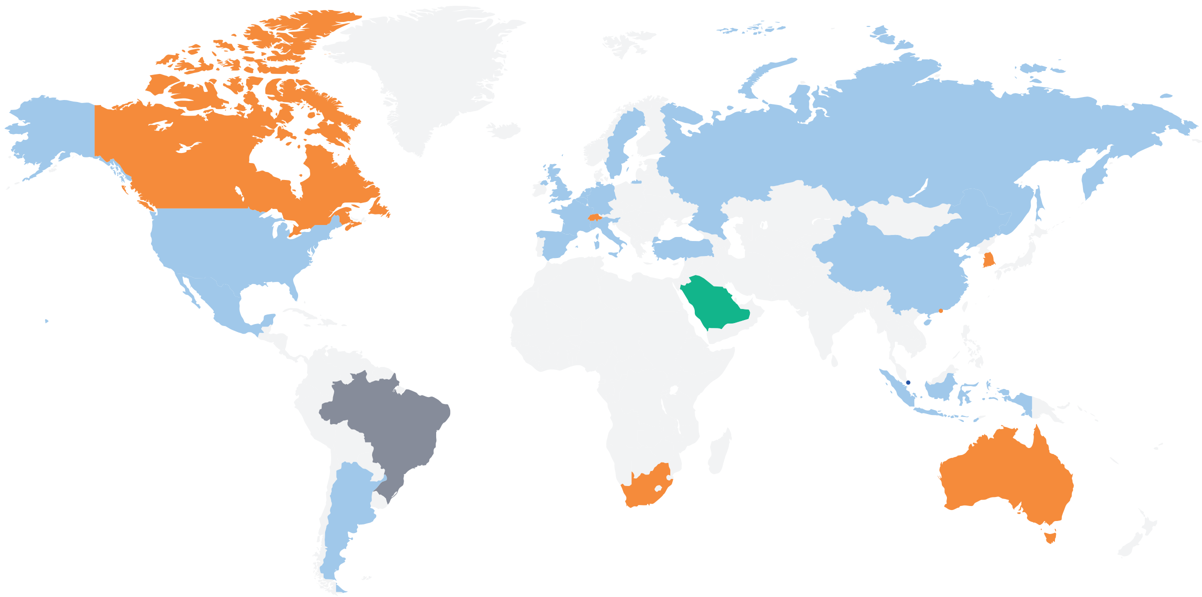
- The initial assessment timelines are considered reasonable, even though not all regulators have yet come up with a final implementation schedule.
- The September 2013 consultative paper issued by the BCBS successfully drew attention from several banks, whose modeling teams then submitted their inputs for incorporation into the final paper.
- The major challenge is posed by the SA-CCR computation data granularity requirements, which are much different from the CEM ones.
- The banks' approach to collateralization is now more driven by the margin reform changes and central counterparty clearing.

Adoption Status

As of March 2016, only the Saudi Arabia Monetary Agency has published a final rule, and only the Monetary Authority of Singapore has published a draft rule.[2] Worldwide adoption status is summarized in Figure 2.

2 BCBS, April 2016.

Figure 2 SA-CCR national regulators' adoption statuses as of March 2016



- Saudi Arabia: Final rule published, takes effect January 1, 2017
- Singapore: Draft published
- Brazil: Final rule to be published
- Australia, Canada, Hong Kong, South Africa, South Korea, Switzerland: Draft to be published
- SA-CCR framework under consideration

Source: BCBS

Basel Committee on Banking Supervision. "Basel III: The standardised approach for measuring counterparty credit risk exposures: Frequently asked questions." BCBS D333. August 2015.

Basel Committee on Banking Supervision. "Foundations of the standardised approach for measuring counterparty credit risk exposures." BCBS WP26. August 2014.

Basel Committee on Banking Supervision. "Tenth progress report on adoption of the Basel regulatory framework." BCBS D366. April 2016.

Basel Committee on Banking Supervision. "The Application of Basel II to Trading Activities and the Treatment of Double Default Effects." BCBS 116. July 2005.

Basel Committee on Banking Supervision. "The non-internal model method for capitalising counterparty credit risk exposures." BCBS 254. June 2013 (rev. July 2013).

Basel Committee on Banking Supervision. "The standardised approach for measuring counterparty credit risk exposures." BCBS 279. March 2014 (rev. April 2014).

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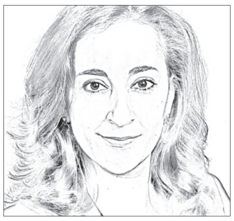

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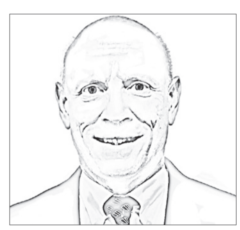

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GLOSSARY OF TERMS

ABS	Asset-backed security
AC	Amortized cost
AFS	Available for sale
AIRB	Advanced internal rating-based
ALLL	Allowance for loan and lease losses
ARIMA	Autoregressive integrated moving average
ARM	Adjustable-rate mortgage
ASU	Accounting Standards Update
BCBS	Basel Committee on Banking Supervision
C&I	Commercial and industrial
CCAR	Comprehensive Capital Analysis and Review
CCF	Credit conversion factor
CECL	Current expected credit loss
CEM	Current exposure method
CLO	Collateralized loan obligation
CMBS	Commercial mortgage-backed security
COREP	Common reporting
CRE	Commercial real estate
DCF	Discounted cash flow
DFAST	Dodd-Frank Act Stress Test
EAD	Exposure at default
EBA	European Banking Authority
ECL	Expected credit loss
EDF	Expected Default Frequency
EL	Expected loss
ERBA	External ratings-based approach
FASB	Financial Accounting Standards Board
FCAG	Financial Crisis Advisory Group
FDIC	Federal Deposit Insurance Corporation
FINREP	Financial reporting
Fintech	Financial technology
FV	Fair value
FV-NI	Fair value through net income
FVO	Fair value option
FVOCI	Fair value through other comprehensive income
FVPL	Fair value through profit or loss
FX	Foreign exchange
GAAP	Generally accepted accounting principles
HELOC	Home equity line of credit
HTM	Held to maturity
IAS	International Accounting Standard
IASB	International Accounting Standards Board
ICAAP	Internal Capital Adequacy Assessment Process
IMM	Internal Model Method
IRB	Internal ratings-based
LGD	Loss given default
LTV	Loan-to-value
M	Maturity
M&A	Merger and acquisition
NCUA	National Credit Union Administration
OCC	Office of the Comptroller of the Currency
OCI	Other comprehensive income
OTTI	Other-than-temporary impairment
P&L	Profit and loss
PCA	Principal components analysis
PCD	Purchased financial assets with credit deterioration
PCI	Purchased credit-impaired
PD	Probability of default
PFE	Potential future exposure
PIT	Point in time
PV	Present value
Q	Qualitative
RC	Replacement cost
RMBS	Residential mortgage-backed security

RRE	Residential real estate
RW	Risk weight
RWA	Risk-weighted asset
SA	Standardized approach
SA-CCR	Standardized approach for counterparty credit risk
SaaS	Software as a service
SATO	Spread at origination
SCCL	Single-counterparty credit limits
SEC	Securities and Exchange Commission
SEC-SA	Securitization standardized approach
SF	Structured finance
SFA	Supervisory formula approach
SM	Standardized method
SSFA	Simplified supervisory formula approach
STC	Simple, transparent, and comparable
STS	Simple, transparent, and standardized
TDR	Troubled debt restructuring
TTC	Through the cycle
VAR	Vector autoregression

Basel ALLL SEC

Forward-Looking

Structured Finance

Stress Testing

Reporting

Finance

Loss Given Default

Expected Loss

Compliance

BCBS

GAAP

Lending

IFRS 9

CECL

Accounting

Probability of Default

Counterparty Mortgage

The Fed

Risk Capital Analysis

IASB Impairment

Data

Exposure Banks