INITIAL CECL ESTIMATES VARY SIGNIFICANTLY

HOW DO WE TACKLE THE ISSUE?

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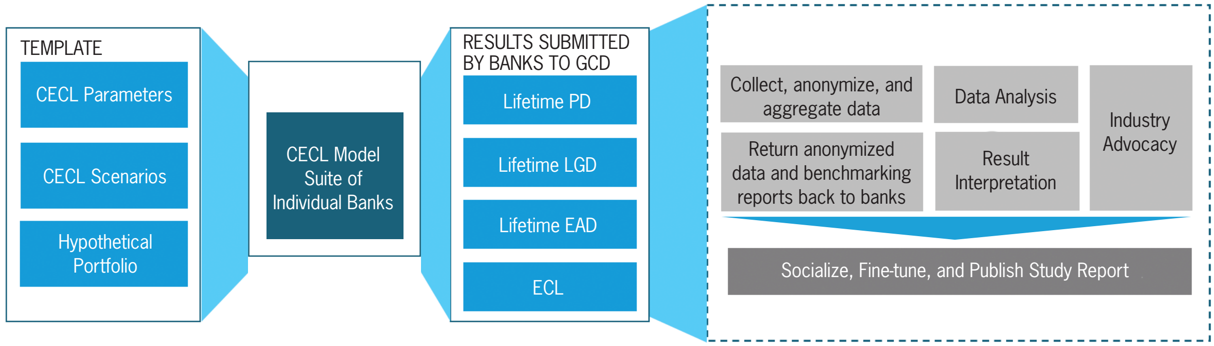
In June 2016, the Financial Accounting Standards Board (FASB) issued a new accounting standard for measuring credit losses for loans and debt securities in the U.S. – Current Expected Credit Losses (CECL). Replacing the earlier Incurred Loss Provisions (ILP) model, CECL will come into effect in 2020 for SEC-registered banks, with implementation staggered thereafter depending on institutions' size.

Expected to have the most significant impact on American banking of any regulatory change since the Dodd-Frank Act, CECL moves the industry away from the backward-looking ILP approach – widely criticized as "too little, too late" for deferring the recognition of losses until it is probable that such losses have occurred – to a more forward-looking approach.

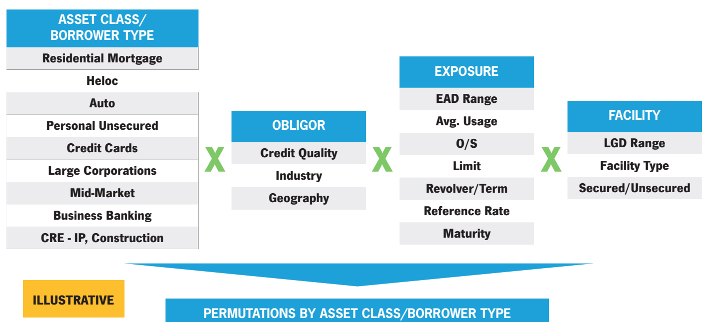
FIGURE 1: CECL BENCHMARKING STUDY PROCESS



CECL, therefore, has a significantly broader scope—requiring a credit loss allowance to be established for the full lifetime of every loan. As a result, banks must use granular data to forecast credit losses using enhanced credit models and macroeconomic predictions—a significant change in terms of both the number and scope of calculations required.

Adapting to this standard as an industry will require a strong model of collaboration. Banks' model outcomes will show a necessary degree of variability to reflect their differing business models and modelling frameworks, while a high degree of variability can be interpreted by regulators as the standard not being effective. Two factors will be key to success in this regard. The first is continued and enriched industry benchmarking to enable banks to check their estimates against those of their peers, identify the causes of variability, and focus in on what constitutes an acceptable level of variability. The second, helped by the first, is to develop standard industry practices in terms of methodologies, ensuring that variability is calculated to reflect variation in business models, rather than simply accidental.

FIGURE 2: HYPOTHETICAL PORTFOLIO



PERMUTATIONS BY ASSET CLASS/BORROWER TYPE	
Residential Mortgage	64
Heloc	16
Auto	32
Personal Unsecured	18
Credit Cards	64
Large Corporations	12
Mid-Market	12
Business Banking	12
CRE - Income-Producing, Construction	4

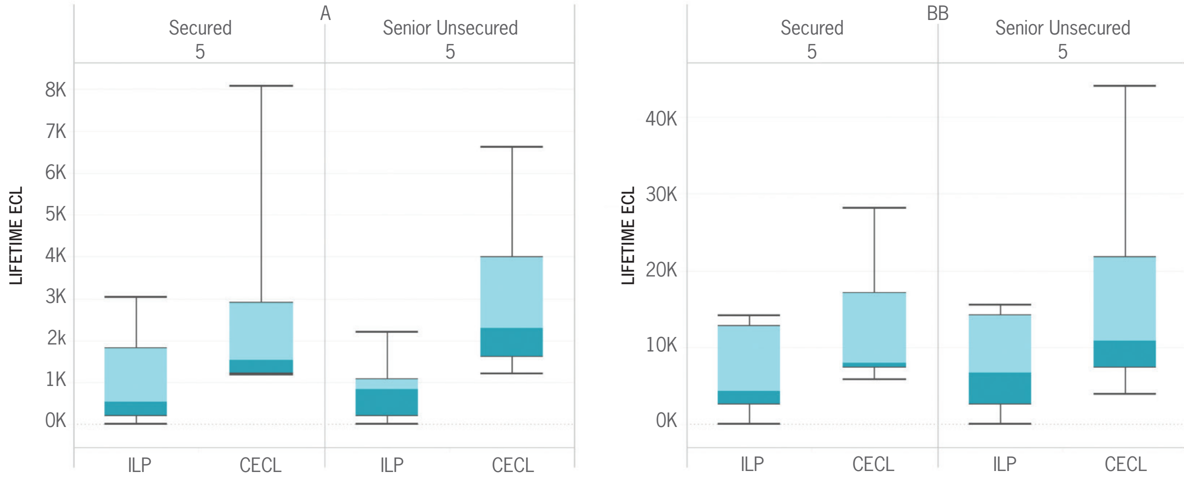
Abundant Variability

Historically, the FASB has taken a rules-based approach to implementing standards. In contrast, CECL is a principles-based accounting standard, leaving many decisions to a bank's own judgment. This flexibility is important—allowing banks to make interpretations in line with their varying business models—but it also means there is currently no "one-size-fits-all" method for calculating CECL. As a result, banks will naturally differ in their modeling choices.

Since CECL is expected to bring forward projection of credit losses, models are also more reliant on forward-looking assumptions, in turn increasing dependence on judgment and forecasts, and leading to elevated variability affecting provisions. This leads also to a difficult assessment of the consistency of CECL frameworks implemented by banks across the board: how do different banks compare? How much variability is consistent and acceptable?

For the standard to be most effective, some calibration will be necessary to ensure this variability in allowances is within acceptable thresholds. Unlike capital and stress-testing, CECL accounting models cannot be tackled effectively by implementing conservative margins or restrictions, and a more prescriptive specification of methodologies would likely restrict the broad range of business

FIGURE 3: LIFETIME ECL UNDER ILP VS CECL FOR A 5-YEAR $2 MILLION TERM LOAN TO A LARGE U.S. CORPORATION



models banks currently employ. This makes determining the level of variability that strikes a balance between flexibility and harmony a matter of significant importance.

Currently, however, there is a lack of readily available data to support a strong case for what that balance should be. Quantitative impact and benchmark studies, which can inform decisions and become a starting point to address concerns such as capital impact issues and procyclicality, can help measure the impact of different modeling choices on CECL estimates, but only a limited number of industry studies are currently available.

A recent Global Credit Data (GCD) and Accenture CECL benchmarking study provided an anonymous benchmarking of banks' estimated credit losses, neutral to their portfolios and macroeconomic forecasts.

The Study

The study brought together 11 banks, asking them to calculate their expected credit losses under CECL— based on a carefully constructed hypothetical portfolio, and representing a range of typical financial assets held by banks. To round out the study, these CECL figures were also calculated against a range of predefined scenarios (such as the CCAR base and stress scenario published by the Federal Reserve) and predefined parameters (such as a given reasonable and supportable forecast period), giving an insight into the impacts on CECL of a variety of different factors.

The hypothetical portfolio included typical banking products, varying in their tenor, credit quality, year of origination, product, and amortization type.

Insights

CECL variability greater than ILP

Results from the benchmarking study confirm, as expected, that there is currently a significant degree of variability in banks' CECL estimates. Tellingly, as shown in Figure 3, the variability between participants' CECL results for a specific hypothetical borrower is significantly higher than for ILP – demonstrating the impact of the new standard on variability. It also showcases that there can and will be outliers when implementing the new standard.

THIS REPORT compiles a set of Benchmark Box Plots to display the variety of the ECL estimates between banks. The graph shows in which range the estimates of the participating banks lie.

HOW TO READ BOX PLOT GRAPHS

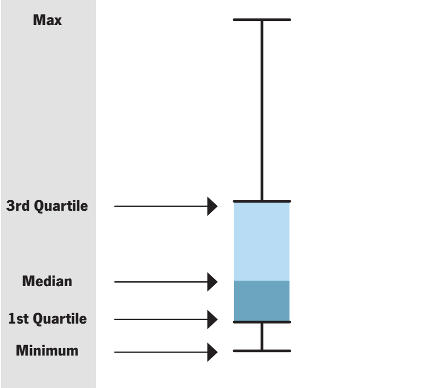
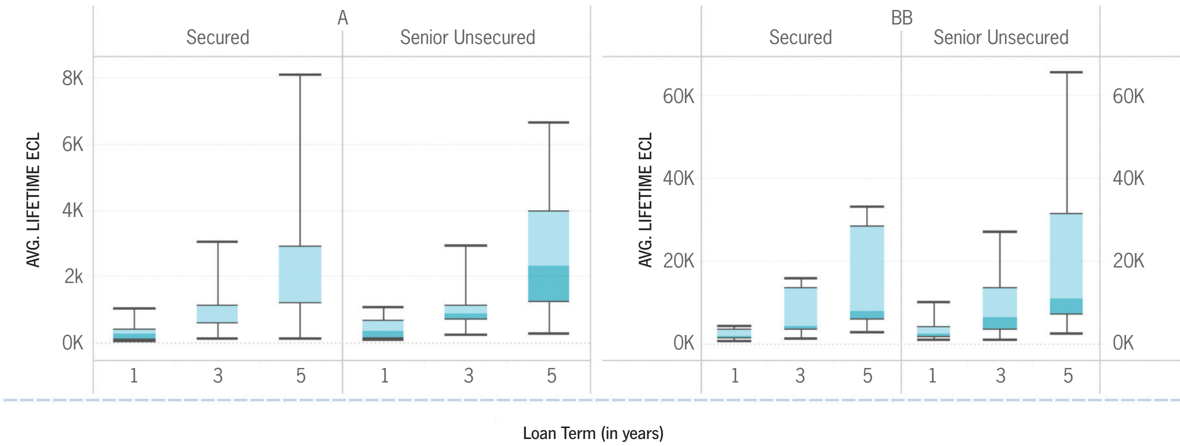


FIGURE 4: LIFETIME ECL FOR A $2 MILLION TERM LOAN TO A LARGE U.S. CORPORATION, VARYING BY CREDIT QUALITY

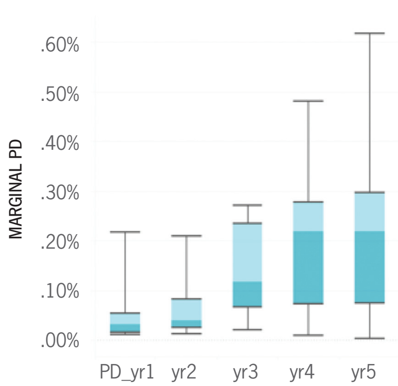


The figure can be read as such: Banks calculate for a five-year term loan of $2 million to an A-rated large U.S. corporate an ILP reserve of anywhere between around $100 (0.5bps) to $3,000 (15bps), while under CECL, they calculate a reserve ranging from around $1,500 (7.5bps) to $8,000 (40bps), where the loan is secured by 90% with equipment and machinery assets. The majority of participating banks (those in the first to third quartiles, see appendix on how to read the boxplot diagrams) calculate a CECL reserve between $1,500 (7.5bps) and $3,000 (15bps) for loans of the same specification – still showing a variability of factor 2 to 3.

The ILP allowance would be significantly lower, but also with less variation between banks. A similar result can be seen for senior unsecured borrowers and a different credit quality (BB).

FIGURE 5: PD VARIABILITY FOR AN A-RATED LARGE CORPORATION BORROWER

PD Across Banks Over Time (Credit Quality A)



Variability Driven by Long Tenors and Low Credit Quality

CECL requires calculating a lifetime expected loss, where – given the difficulties to forecast the future – variability increases along with the tenor of the loan. Figure 4 shows that average lifetime ECL estimates for a $2 million loan to a large, A-rated U.S. corporate vary from almost zero to around $1,000 for a one-year, while estimates for the same loan with a five-year tenor vary between almost zero and $8,000 – an increase of factor 8. This is reflected across both secured and unsecured loans and across different credit qualities.

Another noticeable trend is the increased variability of loans with less-favorable credit ratings. As the credit quality decreases, the variability increases significantly. Figure 4 establishes that for a five-year senior unsecured $2 million term loan, banks' reserves for BB-rated debt (between $5,000 and $65,000) are significantly higher than for A-rated debt (between $500 and $6,500).

Similar results can also be seen in initial benchmarking for IFRS 9, CECL's equivalent for institutions that publish under the IASB's ruled IFRS standard, where, again, banks remain a long way apart in terms of their interpretations of the standard.

What's Driving Variability?

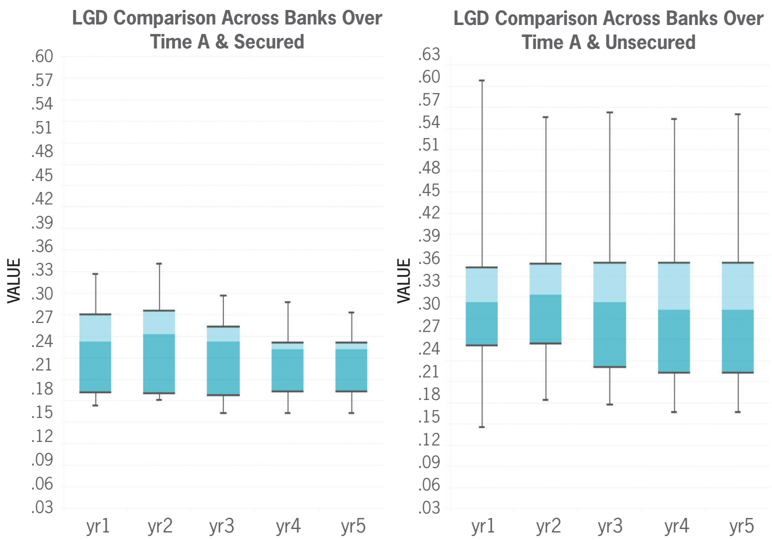
While we can see that factors such as credit quality and loan term affect the variability between banks' CECL estimates, these ultimately can only exaggerate factors already inherent in bank models. So where exactly are models diverging?

To understand this, it is helpful to break CECL down into its constituent parts. Many banks calculate their CECL estimate based on forward-looking probability of default (PD), loss given default (LGD), and exposure at default (EAD) models.

Variability in PD Estimates

The benchmark study reveals that, as with the broader CECL estimate, variability in banks' PD figures increase in line with the tenor of a loan,

FIGURE 6: LGD VARIABILITY OVER TIME



irrespective of its credit rating. Figure 5 shows that while estimates for one-year maturities vary by approximately 20bps, estimates for five-year maturities vary by as much as 60bps.

Even accounting for outliers, the majority of banks still differ significantly when it comes to multi-year PD curves, with a 22bps difference between the upper and lower quartile of the five-year boxplot.

This increase can be put down, at least in part, to the uncertainty of forward-looking estimates. Looking at the study, the lack of common methodologies for estimating longer-term default risk looks to be a major driver of CECL variability.

LGD a Secondary Driver of Variability

Though PD stands out as the main driver of variability, LGD also appears to be a secondary driver, likely driven by different approaches to modeling among banks.

Figure 6 shows, as you would expect, many bank models assume secured LGD is lower (around 23% for a one-year loan to a large corporate) than unsecured (around 29% for the same loan). Outliers aside, LGD estimates demonstrate a reasonable level of variability – though the variability is significantly higher for unsecured than for secured (particularly when you factor in outliers). These can lead to significant differences in CECL, as any change in LGD will directly impact CECL (an increase of LGD by 50%, for example, will increase the corresponding CECL figure by 50% as well).

Unlike PD curves, the majority of banks exhibit stable LGD curves over time – despite the fact these figures are mostly also linked to forward-looking estimates, such as collateral values and exposure profiles.

THOUGH PD STANDS OUT AS THE MAIN DRIVER OF VARIABILITY, LGD ALSO APPEARS TO BE A SECONDARY DRIVER, LIKELY DRIVEN BY DIFFERENT APPROACHES TO MODELLING AMONG BANKS.

Exposure at Default

The study also observed EAD profiles to vary significantly. Again, the main source of variability here is likely the need for forward-looking estimates, with banks making different assumptions as to whether and to what degree borrowers will make prepayments depending on economic conditions.

As Figure 7 shows, projected exposure in the first year varies between 70% to 100% (a range of 30%), while the same projections for the fifth year run from around 0% to 75% (a range of 75%).

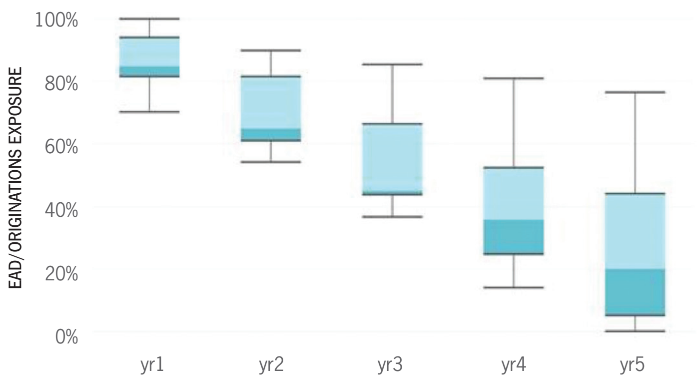
Perspective on the Results

The results of this study represent only a small sample of the total number of banks affected by the switch to CECL. What's more, those banks covered by the study already have fully embedded models in place, meaning they represent a selection of banks more likely than most to be aligned in terms of their CECL estimates. In other words, the true degree of variability between banks when modeling CECL is probably even greater than this study demonstrates.

The Way Forward

Ahead of the CECL implementation day, financial institutions are finding

FIGURE 7: PROJECTED EXPOSURE PROFILE FOR 5-YEAR TERM LOAN



significant challenges in developing their CECL models. As a principles-based approach, little guidance has been provided on methodologies to calculate these estimates and there is little experience to guide banks in computing lifetime loss estimates – a new concept for the industry.

The current level of variability is, therefore, not surprising but, equally, not sustainable, and dilutes the value of standardized risk models. If this persists, regulators may feel they have to step in and impose stricter interpretations – a move that would not be welcomed from the perspective of banks, who will want the freedom to interpret risks in line with their differing business models.

As such, further benchmarking, enabling banks to see how their models stack up against those of their peers, will be crucial to bringing the industry's CECL estimates into a natural alignment without the need for strict supervisory interference. Carrying out further research, data collection, and analysis, involving a greater number of banks, will lead to richer data sets from which a clearer decision can be made in terms of what constitutes an acceptable degree of variability.

This approach, coupled with a close dialogue with regulators to ensure the industry's viewpoint is well represented, will be crucial to the smooth implementation of CECL and to ensuring appropriate regulatory treatment in the future. Ⓡ

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