Variance Compression Bias in Expected Credit Loss Estimates Derived from Stress-Test Macroeconomic Scenarios

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Abstract

Under the IFRS 9 and Current Expected Credit Loss (CECL) standards, credit institutions set the provisions on each asset carried at amortized cost to expected credit losses (ECLs) over a specified horizon. Under IFRS 9, the horizon starts at one year, extending to an asset's lifetime in cases of significant deterioration in credit quality. Under CECL, the horizon is always lifetime.

Some institutions plan to estimate ECLs based on a handful of macroeconomic scenarios of the type that regulators create for testing the adequacy of current capital resources. Such scenarios typically diverge early on, including downturns of varying severities, and converge later toward a long-run average. Due to this convergence, the scenarios depict a future in which, after a year or so, the variability of potential, credit-portfolio outcomes decreases over time and eventually becomes small. This unrealistic, volatility compression imparts a downward bias to ECL estimates for periods beyond a year.

For a wholesale-credit portfolio representative of the population of listed companies, we gauge the size of the bias by comparing ECLs arising from four (or only one) macroeconomic scenario(s) with those obtained from Monte Carlo, credit-factor simulations of the type used in credit-value-at-risk (CVAR) models. Looking out no more than a year, we find little bias in the ECLs obtained as a weighted average of the results from the four, macroeconomic scenarios. But in years two and beyond, the bias turns negative and increasingly so farther out in time. In year two, the downward bias is about 20%; in year four, more than 30%. In the case of only one macroeconomic baseline scenario, the downward bias is about 35% in year one and between 25% and 30% in years two through four. These trials suggest a remedy for the bias: estimate ECLs on the basis of Monte Carlo simulations of credit-factor models. Alternatively, if one has a macroeconomic model that permits Monte Carlo simulation, start with a large number of probabilistic, macroeconomic scenarios that, entered into an expansion (bridge-to-credit factor) model, provide the number and range of credit-factor scenarios needed for unbiased estimation.

Keywords: IFRS 9/CECL, stress testing, variance, volatility, macroeconomic scenarios

1.0. IFRS 9 and CECL Call for Estimation of ECLs over the Life of Each Credit Facility

For unimpaired, financial instruments carried at amortized cost (AC), the International Accounting Standards Board's (IASB's) IFRS 9 standard [1], [2], [3], [4], [5] calls for a loss provision at initial recognition in the amount of the present value (PV) of expected credit losses (ECLs) over a year, with the discounting occurring at the effective interest rate (EIR). Subsequently, the provision remains at the PV of ECLs over a year unless the instrument experiences a "significant increase" in credit risk since initial recognition to a point in excess of "low credit risk." In this case of "significant deterioration," the provision changes to the PV of ECLs over the remaining life of the instrument. Upon identification of impairment, the provision is set, as under the old standard, IAS 39, to the difference between the AC and the PV of anticipated recoveries. Many refer to this tiered process as stage allocation, with stage one involving the one-year ECL, stage two the lifetime ECL, and stage three the discounted-recovery-based provision. Also, stage three differs from the other two in that the cost basis for determining interest revenue changes from the AC to the AC net of the provision.

In the US, the Financial Accounting Standards Board's (FASB's) proposed, Current Expected Credit Loss (CECL) standard doesn't distinguish between stage one and two. Instead CECL always sets the provision on an unimpaired asset to a lifetime one. FASB permits institutions to estimate lifetime ECLs using a variety of techniques, including discounted-cash-flow (DCF) approaches, basically equivalent to the PV-of-ECLs methods under IFRS 9, and loss-rate (LR) approaches, under which the allowance arises as the product of an asset's current AC and a LR expressing lifetime, expected write-offs (WOs) as a percentage of the AC.

The DCF and LR methods differ in that the former involves discounting while the latter generally doesn't. Indeed, the DCF approach, implemented as a PV-of-ECLs method, involves discounting twice, in

- converting future ECLs to PVs as of the reporting date; and
- translating cash flows and other recoveries in default to PVs as of the default date.

This second discounting affects the loss-given default rates (LGDs) involved in the estimation of ECLs. One calculates an LGD as 100% minus the default-time, present value of recoveries divided by exposure at default (EAD): LGD = 100% - PV(recoveries)/EAD. The discounting of recoveries leads to the curious, accounting phenomena of the discount unwind. If the timing and magnitude of anticipated recoveries in a default remain the same, the allowance on a defaulted asset will fall with the passage of time.

Under a LR approach, an institution may find it hard to apply the discounting just described, because WOs by themselves don't pin down the timing of defaults or recoveries. A WO occurs when an institution decides that an outstanding amount is "uncollectable." This may occur at any time after default, including before, at the same time, or after the associated recoveries. Thus, if an institution's default-loss information arises entirely from WOs, it won't be able to emulate a DCF or PV-of-ECLs approach.

In what follows, we emphasize the PV of ECLs approach for determining allowances. For wholesale portfolios of institutions other than community banks, this will likely be the dominant approach. To apply this approach, institutions will need to be able to estimate term structures of ECLs

2.0. Alternative Methods for Estimating ECLs

Below we compare ECLs estimated on the basis of respectively a small number of macroeconomic scenarios of the kind that regulators establish for testing the adequacy of banks' current capital resources and a large number of credit-factor scenarios of the type commonly used in CVAR models.

2.1. ECLs from a Small Number of Macroeconomic Scenarios

Several institutions reportedly plan to use their regulatory, stress-test (ST) models in estimating the ECLs that they use in determining provisions. We illustrate this approach using a ST model that draws on macroeconomic variables (MEVs) that, after suitable transformations, have credible relationships to wholesale-credit conditions. [6], [7], [8], [9], [10], [11], [12]

Applied to the US, the model draws on the MEVs that the Federal Reserve (Fed) uses in characterizing the Comprehensive Capital Analysis and Review (CCAR) scenarios. Only a handful of the CCAR variables have plausible relationships to wholesale credit risk. The model here draws on five: real GDP growth; nominal GDP growth, which together with real GDP determines the GDP deflator; Dow-Jones, total-stock-market index; 10-Year Treasury yield; and the Corporate-BBB yield, which together with the 10-Year Treasury yield determines a BBB spread. The commercial real-estate (CRE) price index is another relevant CCAR variable, influencing CRE default risk. But, in the illustration here, we're focusing on commercial-and-industrial (C&I) and not CRE exposures.

The CCAR variables provide no direct information on business liabilities. Thus, one can't immediately derive indicators of business assets or cash flows *relative* to liabilities or debt service, with such ratios and their associated volatilities being key indicators of corporate default risk. To compensate for missing liability information, the ST model applied here uses selected, CCAR variables together with national-accounts-balance-sheet data from the Fed in estimating an error-correction model (ECM) for non-financial-corporate (NFC) liabilities. Drawing on this ECM along with the CCAR scenarios for equity prices and GDP, the ST model derives, for the NFC sector, scenarios for the ratios of market assets to liabilities and value-added to liabilities as well as for the historical volatilities of those ratios. Dividing the ratios by their respective volatilities and applying a conventional normalization, the ST model derives scenarios for what we call macro-credit, Z indices (macro Zs). These are macro-credit indictors expressed in a form comparable to the credit-factor, industry and region Zs mentioned below, which, in our model, are the direct, systematic drivers of PDs, LGDs, and EADs. The ST model also derives scenarios for a macro Z related to the BBB spread, which provides a direct measure of (risk-neutral) credit risk.

After this, the ST model draws on industry and region, default-risk Zs, obtained by summarizing large samples of listed-company, point-in-time (PIT) PDs from a source such as Moody's CreditEdge (CE) or the Kamakura Merton model. Applying a model that forecasts industry and region Zs on the basis of current and past values of the macro Zs and past values of the industry and region Zs, the ST model obtains scenarios for industry and region Zs. We need this translation of macro Zs to industry and region ones, since only the latter, combined into industry-region-composite indices, serve as systematic-risk factors in the models determining the PDs, LGDs, and EADs of individual, wholesale facilities. This translation to industry and region Zs and the earlier derivation of macro Zs comprise the so-called bridge (or expansion) model in the ST framework (**Figure 1**).

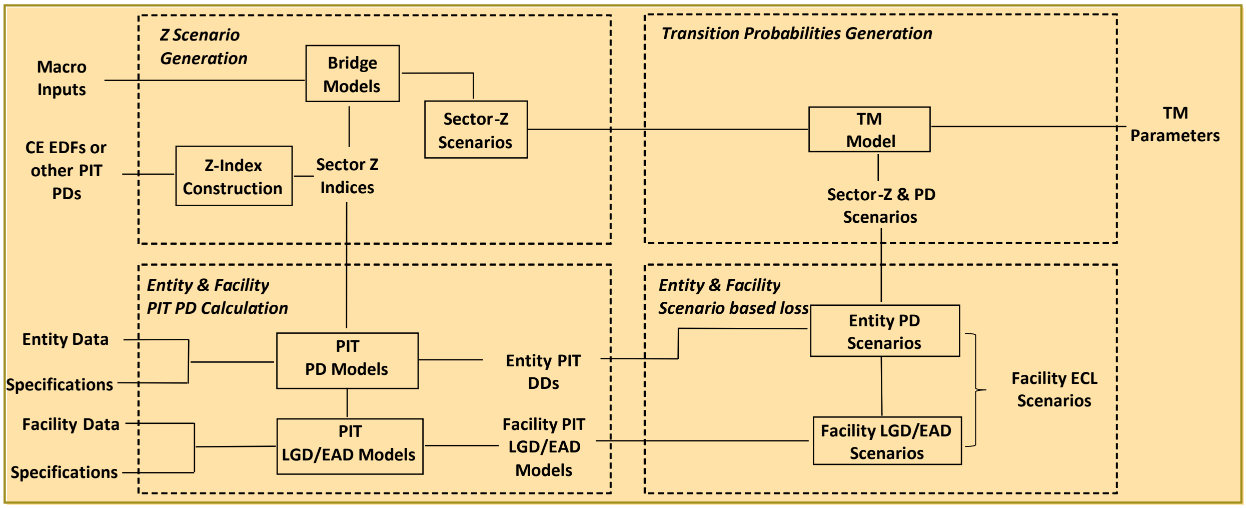

Figure 1: Schematic Representation of ECL Estimation Drawing on MEV Scenarios

Entering the industry and region, Z scenarios into a default-distance-grade (DDG) transition model, the ST model produces multi-period PD scenarios for each of 16, initial DDGs. The ST models draws on these PD-by-DDG scenarios together with the initial, PIT PDs of each entity in deriving, by interpolation, PD scenarios for each entity. The industry and region Z scenarios combined with LGD and EAD models calibrated for each facility produce LGD and EAD scenarios for each facility. Combining the related, entity PD and facility, LGD and EAD scenarios, the ST model delivers ECL scenarios for each facility.

Reiterating, for each scenario, the ST model starts with assumed, equity-price, spread, and GDP paths, draws on a NFC-liability ECM and a host of macroeconomic-variable transformations in producing the related, macro-Z paths, applies a macro-to-industry-and-region, bridge model in deriving the implied, industry, region, and industry-region, Z paths, and enters the industry-region Z paths into a DDG-transition model and facility LGD, and EAD models in producing the ECL scenario for each facility. We run this model below for four scenarios that include the three CCAR-2016 ones and an optimistic scenario added to round out the set as needed in attempting to estimate unconditional ECLs (**Table 1**).

Table 1: MEV Scenarios and the Related, Macro and Industry and Region, Credit-Index Paths through 2019Q1

Category	Item	Scenario	History	Projections						
			2015Q4	2016Q1	2016Q2	2016Q3	2016Q4	2017Q1	2017Q4	2019Q1
Macro Variables	Equity Price % Change	Base	4.02%	1.11%	1.13%	1.18%	1.18%	1.14%	1.19%	1.11%
		Optimistic	4.02%	6.00%	12.00%	15.00%	10.00%	5.00%	1.20%	2.00%
		Adverse	4.02%	-0.96%	-12.44%	-10.03%	-7.18%	1.34%	4.29%	2.92%
		Severely Adverse	4.02%	-22.60%	-23.89%	-14.47%	-9.83%	7.30%	10.73%	6.69%
	BBB Spread	Base	2.40	2.10	2.10	2.10	2.00	2.00	1.90	1.80
		Optimistic	2.40	1.80	1.00	1.00	1.10	1.30	1.80	1.80
		Adverse	2.40	3.10	3.50	3.60	3.70	3.60	3.10	2.60
		Severely Adverse	2.40	4.60	5.20	5.60	5.80	5.40	4.40	3.00
	Real GDP Growth	Base	1.38%	2.50%	2.60%	2.60%	2.50%	2.40%	2.30%	2.10%
		Optimistic	1.38%	2.50%	3.20%	4.00%	3.50%	2.70%	2.10%	2.20%
		Adverse	1.38%	-1.50%	-2.80%	-2.00%	-1.10%	0.00%	2.60%	3.00%
		Severely Adverse	1.38%	-5.10%	-7.50%	-5.90%	-4.20%	-2.20%	3.00%	3.90%
Macro Zs	Corp Assets-to-Debt Z	Base	1.42	1.32	1.24	1.17	1.11	1.05	0.92	0.79
		Optimistic	1.42	1.33	0.92	0.49	0.53	0.68	1.01	1.01
		Adverse	1.42	1.22	-0.07	-0.64	-0.90	-0.82	-0.55	-0.07
		Severely Adverse	1.42	-1.20	-2.18	-2.46	-2.57	-2.41	-1.89	-1.00
	BBB Spread Z	Base	-0.10	0.43	0.43	0.43	0.62	0.62	0.81	1.02
		Optimistic	-0.10	1.02	3.15	3.15	2.82	2.23	1.02	1.02
		Adverse	-0.10	-1.15	-1.67	-1.79	-1.91	-1.79	-1.15	-0.42
		Severely Adverse	-0.10	-2.89	-3.46	-3.81	-3.98	-3.64	-2.68	-1.02
	Macro Z Total	Base	0.66	0.87	0.83	0.80	0.86	0.83	0.87	0.91
		Optimistic	0.66	1.18	2.04	1.82	1.68	1.46	1.02	1.02
		Adverse	0.66	0.03	-0.87	-1.22	-1.40	-1.31	-0.85	-0.25
		Severely Adverse	0.66	-2.05	-2.82	-3.14	-3.28	-3.03	-2.29	-1.01
Industry & Region Zs	NA Corp	Base	-0.86	-0.71	-0.67	-0.65	-0.53	-0.47	-0.25	0.02
		Optimistic	-0.86	-0.51	0.17	0.18	0.21	0.12	-0.18	0.02
		Adverse	-0.86	-1.28	-1.90	-2.24	-2.39	-2.30	-1.64	-0.70
		Severely Adverse	-0.86	-2.68	-3.43	-3.88	-4.03	-3.79	-2.77	-1.12
	Machinery & Equipment	Base	0.72	0.60	0.47	0.42	0.45	0.44	0.49	0.53
		Optimistic	0.72	0.74	1.06	1.08	1.09	0.99	0.52	0.45
		Adverse	0.72	0.22	-0.42	-0.81	-1.07	-1.11	-0.67	0.11
		Severely Adverse	0.72	-0.73	-1.58	-2.17	-2.47	-2.40	-1.56	-0.07
	NA Corp Machinery & Equipment	Base	-0.24	-0.19	-0.23	-0.23	-0.15	-0.11	0.05	0.24
		Optimistic	-0.24	-0.01	0.55	0.57	0.59	0.49	0.10	0.20
		Adverse	-0.24	-0.71	-1.37	-1.75	-1.95	-1.91	-1.31	-0.39
		Severely Adverse	-0.24	-1.99	-2.82	-3.34	-3.56	-3.39	-2.39	-0.73

Note: The scenarios used in this paper begin in 2016Q1 and continue for four years, ending in 2019Q4. Due to space limitations we show values above only out to 2019Q1.

See below the formulation of the debt (**Table 2**) and bridge (**Table 3**) models used in this paper. The debt model has an ECM form, with short-run dynamics together with a long-run relationship under which debt converges gradually to a particular (time varying) ratio to GDP. The bridge model has a broadly similar formulation. It assumes that the industry or region Z reverts toward the economy-wide average represented by the macro Z, which here is a simple average of the NFC asset-to-liability and BBB-spread Zs. Observe that typically over several years, the macro Z and thus the related industry or region Z approaches its long-run average value of zero. Besides that the model includes dynamics under which the industry or region Z moves in the same direction as recent changes in the macro Z and lagged changes in the industry or region Z. We've estimated both the debt and bridge models by ordinary-least-squares (OLS) regression. The debt-model estimation draws on quarterly national-accounts data from 1980 to 2015. The bridge-model estimation draws on quarterly data over 1990-2015 with pooling across the different industries (20 in number) and regions (12 in number).

Table 2: Debt Model Used in this Paper

Variable Type	Variable	Coefficient
Dependent	Quarterly Change NFC Liabilities	NA
Explanatory	NFC Liabilities minus NFC-Liabilities Target (= 0.97 x GDP)	-0.07
	Quarterly Change in GDP	0.34
	Quarterly Change in NFC Liabilities Lagged One Quarter	0.30
	Quarterly Change in NFC Liabilities Lagged Two Quarters	0.28

Note: All variables occur as deviations from sample means divided by the respective, sample standard deviation. Liability target determined in first-stage estimation of long-run relationship between NFC liabilities and GDP.

Table 3: Bridge Model Used in this Paper

Variable Type	Variable	Coefficient
Dependent	Quarterly Change in Industry or Region Z	NA
Explanatory	Industry or Region Z Lagged One Quarter	-0.07
	Macro Z Lagged One Quarter	0.04
	Quarterly Change in Macro Z	0.67
	Quarterly Change in Macro Z Lagged One Quarter	0.10
	Quarterly Change in Macro Z Lagged Two Quarters	0.07
	Quarterly Change in Industry or Region Z Lagged One Quarter	0.02
	Quarterly Change in Industry or Region Z Lagged Two Quarters	0.02
	Quarterly Change in Industry or Region Z Lagged Three Quarters	0.05

The ST model just described performs well in one-year back tests, producing results close to the high losses in stress times and the low losses in boom times. Thus, this model together with the CCAR scenarios seems well suited for the task of evaluating the adequacy of an institution's current capital resources. However, we find the approach problematic if applied in estimating the ECLs needed for determining IFRS 9 or CECL provisions.

The problems trace to the small number of scenarios of the kind that the regulators provide for testing the adequacy of current capital resources. Such scenarios typically diverge early on, including downturns of varying severities, and converge later toward a long-run average (**Figure 2** and **Figure 3**). Due to this convergence, the scenarios depict a future in which, after a year or so, the variability of potential, credit outcomes decreases over time and eventually becomes small. As we'll see, this unrealistic, volatility compression imparts a downward bias to ECL estimates for periods beyond a year.

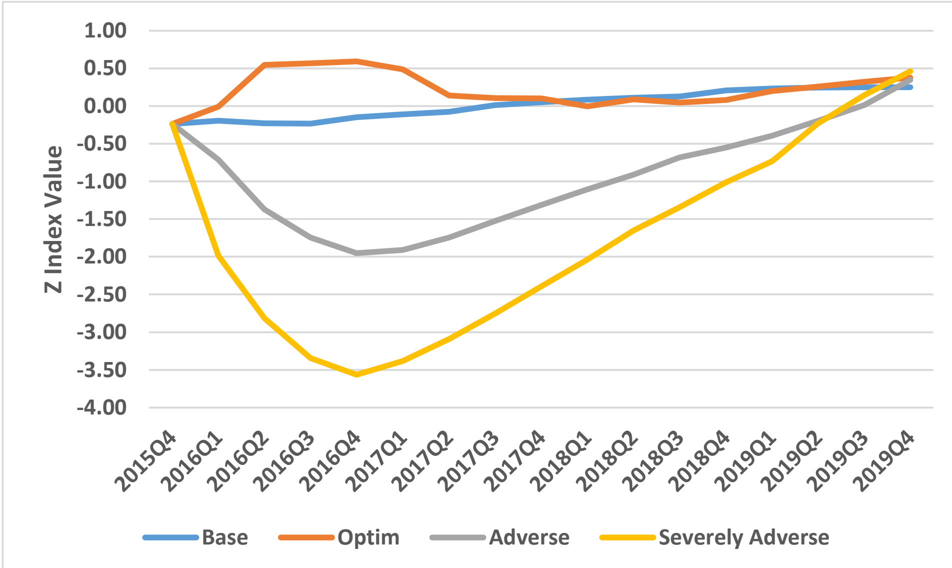

Figure 2: North American, Machinery and Equipment Z Paths Implied by Four Macroeconomic Scenarios

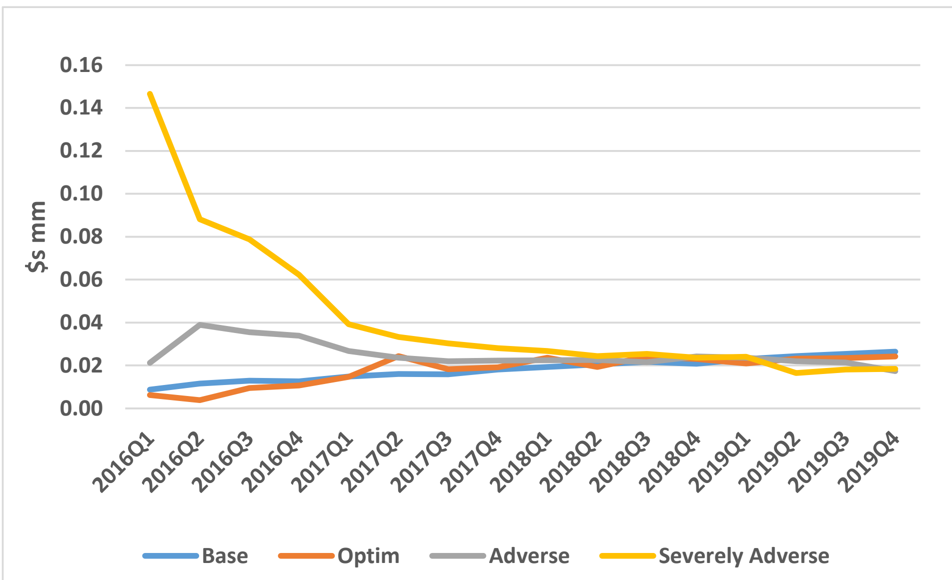

Figure 3: ECL Term Structures Implied by Four Macroeconomic Scenarios: Four-Year RCF to a BB-rated Borrower in the North American Machinery and Equipment Industry

2.2. ECLs from a Large Number of Credit-Factor Scenarios

To determine the effect of volatility compression on ECLs, we compare results from the above approach with those that arise from Monte Carlo simulations of credit-factor models. As shown in **Figure 4**, we apply all of the modeling components already depicted in **Figure 1** with the exception of the bridge model

[6], [7], [8], [9], [10], [11], [12]. In this case, the Z scenarios for industries and regions arise not from MEV scenarios bridged to industry and region ones, but from so-called mean reversion and momentum (MM) based models.

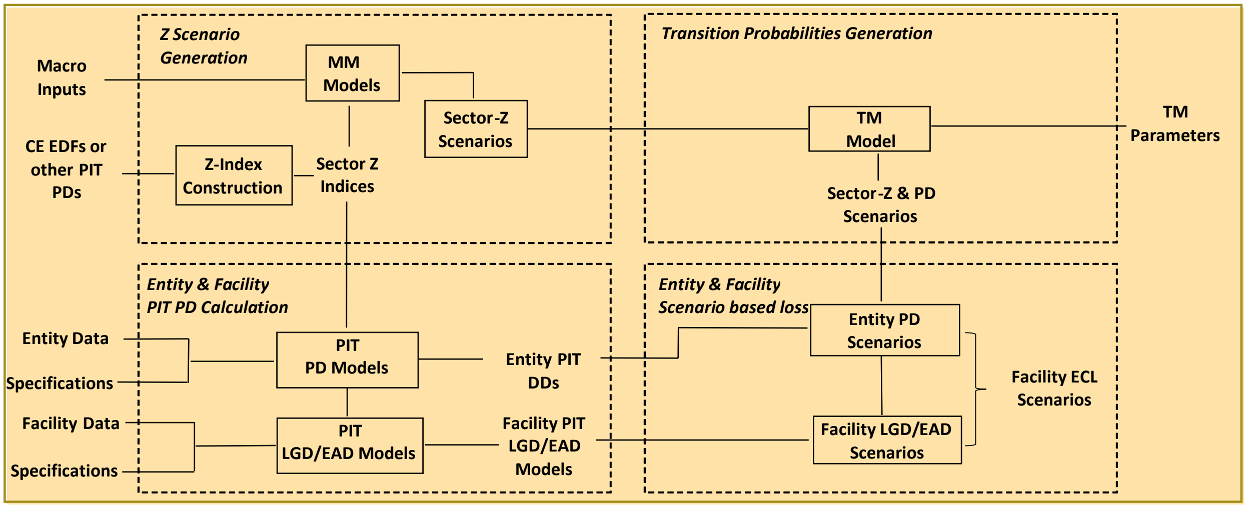

Figure 4: Schematic Representation of ECL calculations using Monte-Carlo Credit-Factor Scenarios

The MM models are second-order-autoregressive (AR(2)), time-series models drawing on past industry and region, Z values. In these models, Z values evolve under the influence of mean reversion, a tendency for Z to gravitate to its long-run average value of zero, momentum, a tendency for Z to continue changing in the same direction as recently, and random shocks. On account of the presence of mean-reversion and momentum, we refer to these AR(2) models as MM models. See below the formulation of the MM models applied in this paper (**Table 4**). The coefficient estimates arise by OLS regression conducted separately for each of 20 industries and each of 12 regional groupings. In the trials described in this paper, we use only the models for the machinery-and-equipment industry and the North American-NFC, regional grouping

Table 4: Formulation of the MM Models Used in this Paper

Industry or Region	Variable Type	Variable	Coefficient
Machinery and Equipment Industry	Dependent	ΔZ	NA
	Explanatory	Z Lagged One Quarter	-0.11
		ΔZ Lagged One Quarter	0.25
	Residual	Normalised Shock	0.43
North American Region (Non-Financial Firms)	Dependent	ΔZ	NA
	Explanatory	Z Lagged One Quarter	-0.07
		ΔZ Lagged One Quarter	0.23
	Residual	Normalised Shock	0.44

To produce scenarios using an MM model, one begins by drawing random normal shocks. Each time series of shocks, scaled properly (by the normalised shock coefficient) and entered into the model, generates a possible, future Z path. Repeating this process many times, one gets a large number of Z paths representative of the probability distribution of such paths (**Figure 5**). In contrast with the earlier scenarios derived from macroeconomic assumptions, one obtains a granular representation of a symmetrical distribution that grows over time in variability while approaching an asymptotic, stationary variance. The corresponding ECL scenarios provide a detailed representation of an asymmetric distribution that also grows in variability early on while approaching an asymptotic stationary variance (**Figure 6**). Here we display ECL scenarios for a revolving credit facility (RCF) with remaining maturity of four years. The hypothetical borrower is a BB-rated company in the machinery and equipment industry located in North America.

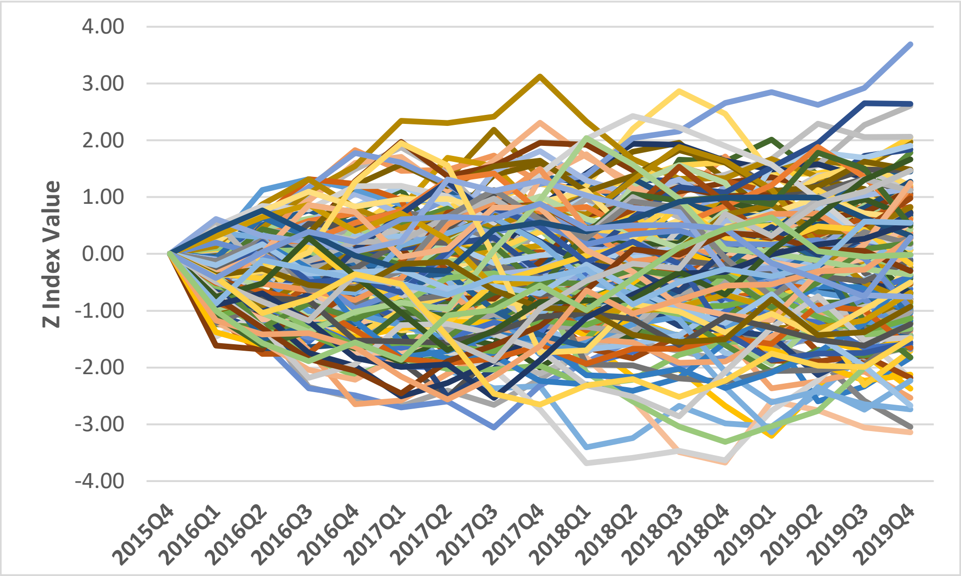

Figure 5: Sector-Z Paths from Monte-Carlo Simulation of Credit-Factor Models

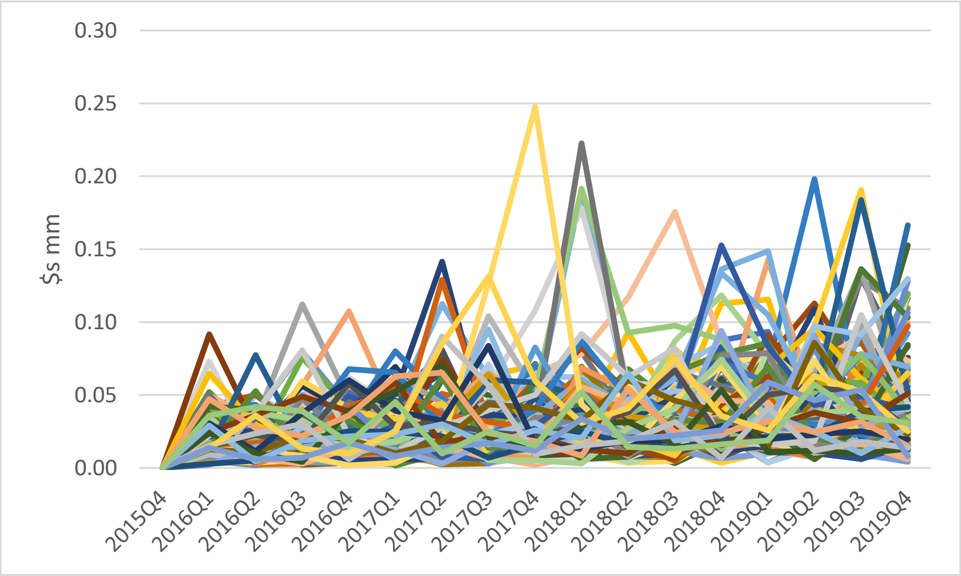

Figure 6: ECL Scenarios Derived from Monte Carlo Credit-Factor Simulations

2.3. Z Volatilities over Time under the Two Approaches

Before comparing the ECL estimates, we first examine the cross-scenario, Z volatilities under the two approaches (***Figure 7***). The three, regulatory scenarios together with a fourth, counterbalancing optimistic one offer an unconvincing depiction of the term structure of credit risk, with the cross-scenario, Z volatility collapsing after about a year. Clearly, regulatory scenarios designed to test the adequacy of current capital resource don't provide realistic descriptions of term risk. The Monte Carlo Z-factor scenarios, in contrast, provide a plausible depiction of term risk, with the cross-scenario, Z standard deviation rising at a progressively declining rate with the curve resembling a square root of tenor graph.

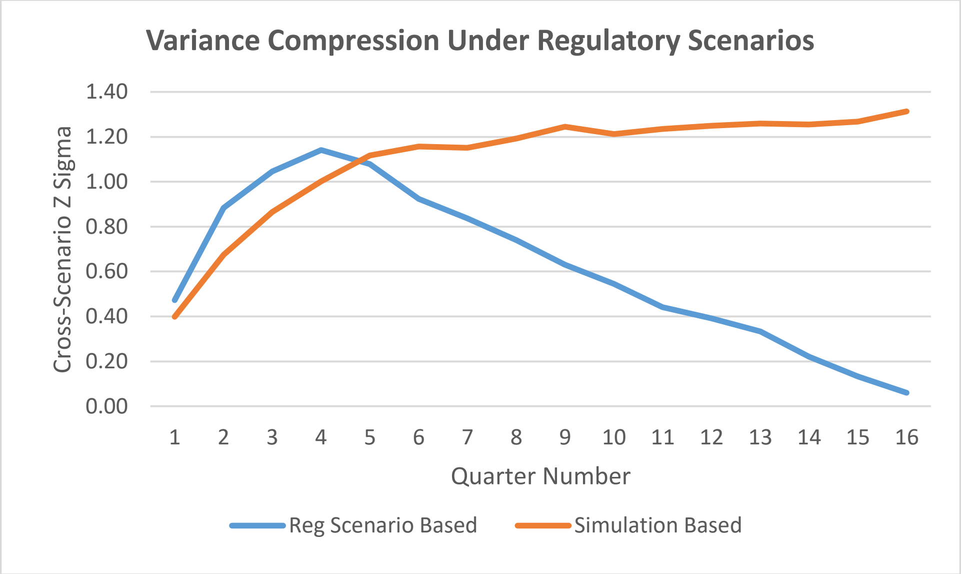

Figure 7: Comparison of Cross-Scenario, Z Standard Deviations

2.4. Comparison of ECLs under the Two Approaches

We now quantify the effect on ECLs. For a portfolio of several, wholesale-credit facilities, we compare ECLs arising from four (or only one) macroeconomic scenario(s) with those obtained from Monte Carlo, credit-factor simulations produced by MM models.

2.4.1. Trial Credit Portfolio

The credit portfolio in the trials includes a mixture of ratings and facility types (**Table 5**) chosen to be broadly representative of US C&I loan exposures. While the distinct ratings and facility types are smaller in number than those at most banks and the utilization of RCFs higher than in the case of many, large-corporate facilities, the portfolio overall has a TTC, one-year loss rate relative to book value of about 0.83%, close to the long-run average for the US-bank, C&I loan book. To keep the example simple, each entity in the portfolio is classified as a North American, machinery-and-equipment business and each facility has a remaining maturity of four years.

Table 5: Selected Attributes of Credit Portfolio Used in the Trials

S&P TTC Rating	TTC One-Year PD	Share of Total Limit	Facility Type	Non-Default Utilization	Expected TTC LGD	Expected TTC CCF
A	0.05%	16%	$30 mm RCF	60%	40.5%	30.9%
			$30 mm TL	100%	40.5%	100.0%
BBB	0.17%	21%	$30 mm RCF	60%	40.5%	30.9%
			$30 mm TL	100%	40.5%	100.0%
BB	0.72%	29%	$30 mm RCF	60%	40.5%	30.9%
			$30 mm TL	100%	40.5%	100.0%
B	4.04%	34%	$30 mm RCF	60%	40.5%	30.9%
			$30 mm TL	100%	40.5%	100.0%

2.4.2. ECL Results

Looking out no more than a year, we find little bias in the ECLs obtained as a weighted average of the results from the four, macroeconomic scenarios (**Figure 8**). Indeed, we adjusted the scenario weights, within reasonable bounds, to ensure this result. But in year two and beyond, the bias turns negative and increasingly so farther out in time. In year two, the downward bias is about 20%; in year four, more than 30%. In the case of only one macroeconomic baseline scenarios, the downward bias is about 35% in year one and between 25% and 30% in years two through four.

These results involve a hypothetical portfolio of credit facilities. Consistent with the full, historical sample of CreditEdge EDFs, the portfolio has the following, Standard and Poor's (S&P)-equivalent, TTC-grade distribution: A: 16%; BBB: 21% BB: 29% B: 34%. Each of the facilities has a remaining maturity of four years and a limit (not amortizing) of $30 million. Half of the facilities are term loans (TLs) and the rest RCFs. All have (DT) LGDs of 45% and DT CCFs of 45%. The RCFs have expected utilization other than in default of 60%. For this exercise, we assume that all of the borrowers are industrial-machinery firms located in North American.

In calculating the average of ECLs from the four macroeconomic scenarios, we apply weights of 50% to the baseline, 25% to the optimistic scenario, 20% to the adverse, and 5% to the severely adverse. This symmetrical weighting provides a plausible basis for approximating an unconditional ECL or, more likely, a slightly upwardly biased result.

Figure 8: Alternate Estimates of Yearly ECLs for a Portfolio of Four-Year-Maturity Loans

2.5. Remedies for Downward Bias in Estimates Derived from Macroeconomic Scenarios

The above trials suggest an obvious remedy for the volatility-compression bias: estimate ECLs on the basis of Monte Carlo simulations of credit-factor models. Alternatively, if one has a macroeconomic model that permits Monte Carlo simulation, one could start with a large number of probabilistic, macroeconomic scenarios that, entered into an expansion (bridge-to-credit factor) model, provide the number and range of credit-factor scenarios needed for unbiased estimation. This would surely produce a profile of scenarios broadly similar to that from the credit-factor Monte Carlo simulations.

3.0. Summary

Several institutions plan to estimate ECLs drawing on a handful of macroeconomic scenarios of the type that regulators create for testing the adequacy of current capital resources. Such scenarios often diverge early on, including downturns of varying severities, and converge later toward a long-run average. Due to this convergence, the scenarios depict a future in which, after a year or so, the variability of potential, credit outcomes decreases over time and eventually becomes small. This unrealistic, volatility compression imparts a downward bias to ECL estimates for periods beyond a year.

For a wholesale-credit portfolio representative of the population of listed companies, we estimate the size of the bias by comparing ECLs arising from four (or only one) macroeconomic scenario(s) with those obtained from Monte Carlo, credit-factor simulations of the type used in CVAR models. Looking out no more than a year, we find little bias in the ECLs obtained as a weighted average of the results from the four, macroeconomic scenarios. But in years two and beyond, the bias turns negative and increasingly so farther out in time. In year two, the downward bias is about 20%; in year four, more than 30%. In the case of only one macroeconomic baseline scenario, the downward bias is about 35% in year one and between 25% and 30% in years two through four. These trials suggest a remedy for the bias: estimate ECLs on the basis of Monte Carlo simulations of credit-factor models. Alternatively, if one has a macroeconomic model that permits Monte Carlo simulation, one could start with a large number of probabilistic, macroeconomic scenarios that, entered into an expansion (bridge-to-credit factor) model, provide the number and range of credit-factor scenarios needed for unbiased estimation.

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