Sageworks Advisory Services

PRACTICAL CECL™ CASE STUDIES – HIDDEN COMPLEXITIES OF SIMPLE APPROACHES FOR COMMUNITY INSTITUTIONS

EXECUTIVE SUMMARY

The CECL standard grants institutions broad latitude in the data and information used in measurement; the standard is non-prescriptive in methodologies to be used (though does go so far as to enumerate several sensible options). A great deal of content from the supervisory and accounting communities, as well as other practitioners, focuses on simple analyses that are mentioned in the standard – loss-rate and vintage approaches are commonly discussed.

It has not been our experience that these simple approaches will produce meaningful results for many community financial institutions. This finding is not an issue with the conceptual underpinnings of the approaches, rather, it stems from core statistical realities that apply to typically conservative community institutions.

In this paper, we examine just such an institution; we first examine problems with loss-rate approaches, and then construct a defensible projection of lifetime credit loss without meaningful first-party losses or historical loan-level detail.

APPLICABLE GUIDANCE[1]

FASB Accounting Standards Update Topic 326 (CECL):

> *An entity may use discounted cash flow methods, loss-rate methods, roll-rate methods, probability-of-default methods, or methods that utilize an aging schedule. An entity is not required to utilize a discounted cash flow method to estimate expected credit losses. Similarly, an entity is not required to reconcile the estimation technique it uses with a discounted cash flow method*
>
> **p109, 326-20-30-3**

> *The measurement of expected credit losses is based on relevant information about past events, including historical experience, current conditions, and reasonable and supportable forecasts that affect the collectibility of the reported amount. An entity must use judgment in determining the relevant information and estimation methods that are appropriate in its circumstances.*
>
> **p2**

> *When developing an **estimate** of expected credit losses on financial asset(s), an entity shall consider **available** information relevant to assessing the collectibility of cash flows. This information may include internal information, **external information, or a combination of both** relating to past events, current conditions, and reasonable and supportable forecasts*
>
> **p110, 326-20-30-7, emphasis ours**

> *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.*
>
> **p111, 326-20-30-10**

[1] https://asc.fasb.org/imageRoot/39/84156639.pdf

INTRODUCTION

In this case study, we will once again examine Rocket Bank. Rocket Bank is a New England institution with little observable loss experience in the recent past, and carries an Allowance-to-Loans ratio of approximately 1.0% under today's incurred loss notion; this 1.0% is achieved using an anchored qualitative approach. As is common in the Mid-Atlantic, New England, and certain western coastal markets, the portfolio is comprised of a small number of larger loans.

We will first assess the applicability of several "simple" approaches to Rocket Bank's largest portfolio, a Commercial Real Estate pool. We will perform this assessment without relying on loan-level details to "truly" run these simple approaches, utilizing top-down data from the FFIEC call report filings.

Following this assessment, we will demonstrate how a layering of peer experience and a more sophisticated modeling approach will produce stable, predictable, defensible allocation, even in the absence of observable first-party loss in a performing environment. Our approach is not *simple*; it is, however, *practical*.

After reviewing this case study, readers should be able to:

- Understand whether a loss-rate approach will produce meaningful results for their institution
- Assess the cost and benefit of collecting additional historical data to implement e.g. a vintage or loss-rate analysis
- Defend the use of peer experience in credit loss modeling

RELATED MATERIALS

Readers interested in a more detailed description of our approach should review the Practical CECL™ Transition Guide chapters on loss driver analysis, expedients vs. cash flows, and peer and industry data. A companion guide of benchmark cashflow results may also be of use to auditors, regulators, or financial institution practitioners.

CASE STUDY PORTFOLIO

The portfolio under consideration comprises a Commercial Real Estate portfolio of projects in the New England area; it is composed of about 300 loans representing a stated exposure of $600MM. Further parameters of the portfolio are presented, below.

PARAMETER	VALUE	COMMENTS
Balance	$600,000,000	We will assume this balance represents amortized cost in this exercise.
Loan Count	300	This is a typical count of a portfolio of this size in this region, with an average exposure of $2.0MM
Contract Life	9 Years	This is a longer leash than we might typically see, but most structures have reprice options for Rocket Bank
Average Coupon Rate	4.1%	Annualized interest rate, on average
Average Amortization Length	25 Years	Used to derive payment expectations
Weighted Average Life	4.5 Years	Bottom-up analysis with explicit prepayment and default input was used to produce this expectation.
Net Deferred Fees + Unamortized Premiums (Discounts)	Not Material	No purchased assets exist in the portfolio.
Constant Prepayment Rate	12%	Annually, 12% of the pool balance is collected in addition to contract principal

INITIAL ASSESSMENT: LOSS-RATE APPROACH

Without collecting loan-level details, we can perform an initial assessment of the loss-rate expedient. We reproduce below annual FFIEC call report data on losses and recoveries for the segments under consideration.

	17	16	15	14	13	12	11	10	09	08
1.d.A Secured by multifamily (5 or more) residential properties (Charge-offs)	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0
1.d.B Secured by multifamily (5 or more) residential properties (Recoveries)	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0
1.e.1.A Loans secured by owner-occupied nonfarm nonresidential properties (Charge-offs)	$0	$0	$0	$0	$0	$0	$0	$0	$35	$0
1.e.1.B Loans secured by owner-occupied nonfarm nonresidential properties (Recoveries)	$0	$0	$0	$3	$2	$4	$0	$1	$4	$0
1.e.2.A Loans secured by other nonfarm nonresidential properties (Charge-offs)	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0
1.e.2.B Loans secured by other nonfarm nonresidential properties (Recoveries)	$0	$0	$4	$0	$0	$0	$0	$0	$0	$0

The "open pool" method, as described in some third-party materials, represents the most conceptually simple method of loss estimation under the CECL notion. To avoid confusion, we will refer to this method as a "cumulative" analysis. Under this method, we consider the cohort of loans in a pool as of some date (the "measurement date"). We then look forward some amount of time (the "analysis period") and total up losses that accrue **only to loans that existed in the cohort at the measurement date**. This summation of loss is divided into the balance (or amortized cost basis) of loans in the cohort at the measurement date, as of the measurement date, to produce a cumulative loss rate for the measurement date.

This cohort concept is critical to understand: if a loss accrues to a loan that did not exist as of the measurement date, it should be ignored in the loss-rate for that measurement date. This is one of the primary reasons top-down data cannot be used to compute a cumulative rate; there is no way to determine that the loss should or should not be included in the numerator to the starting balance: this will cause us to overstate our loss rate, potentially severely, when using top-down data to perform this method.

While use of a top-down expedient to a cumulative approach method would not be representative of actual loss-rate outputs, we can still use it to inform our decision making early in the implementation process: having a rough idea of what a model output would be can be useful in deciding what models to apply.

With that in mind, we will perform a top-down estimation using Sageworks proprietary Napkin Technology™; these are the same robust tools and rigorous controls the Sageworks Advisory Services team uses early in some implementations:

$$\text{Loss Rate}_{2012} = \frac{\sum_{2012}^{2108\ Q2} \text{Chargeoffs (CRE)}}{\text{Balance}_{2012}\ \text{CRE}} = \frac{\$0}{\text{Doesn't Matter}} = 0\%$$

In this estimation, we sum chargeoffs from 2012 through Q2 2018, representing a life-of-loan measurement (4.5 years weighted average life). It is worth noting that for this longer-duration pool, we would require bottom-up data *beginning* in 2012 to produce a single data point, even if there were meaningful losses to observe. We can, of course, apply this same first-order approximation on recessive conditions to determine if there is a higher anchor point. We examine Rocket Bank's loss experience against it's smaller CRE portfolio in 2008. Note that we are calculating a gross chargeoff rate, not a net chargeoff rate (we exclude recoveries):

$$\text{Loss Rate}_{2008} = \frac{\sum_{2008}^{2102\ Q2} \text{Chargeoffs (CRE)}}{\text{Balance}_{2008}\ \text{CRE}} = \frac{\$35}{150{,}000} = .00023 = 2.3\ \text{bp}$$

It is immediately apparent that Rocket Bank will not be able to use loss-rate approaches to produce meaningful results. If this discussion is a bit facile, it is by intention; this is the most common problem the community banks we have worked with have faced in this exercise and solving it is the core purpose of the Practical CECL™ approach.

Use of a loss-rate approach, whether risk-rated or not, will likely produce results that require an institution to use qualitative adjustment (and, as with Rocket Bank, potentially *only* qualitative adjustment) to achieve reserve levels that management and external audiences would deem adequate. While a purely subjective allocation model may be attracted to very specific stakeholders at very specific times, it is our opinion that such an approach will not be attractive to any audience with accountability to the Public Company Accounting Oversight Board.

Rocket Bank's problem in this case is *numerical*; if Rocket Bank could make 5,000 more loans of identical character to its existing book, Rocket Bank would have observed a convergent, meaningful loss rate over this time period. Similarly, credit risk is easier to measure when it is more present, but we would not recommend Rocket Bank start taking on more marginal credits to ease its risk modeling practices. It is worth noting that some institutions experience this *numerical* problem in the inverse, where a single large relationship produces outlandish loss expectations.

INITIAL ASSESSMENT: VINTAGE APPROACH

In a vintage analysis, we essentially desire to compute point-in-time loss rates for closed cohorts of loans grouped by origination year (or renewal/policy year). Vintage analysis is theoretically robust for assets where:

- Note structure is homogenous
- Credit risk is homogenous
- Credit risk is detectable based on past experience, either through volume of lending or risk profile of the pool
- Collateral depreciation outpaces amortization

To wit, a pool of 10,000 3-year auto loans would be an excellent candidate for vintage evaluation. We can use our Napkin Technology to determine the vintage curve as evaluated for this pool of 300 CRE loans:

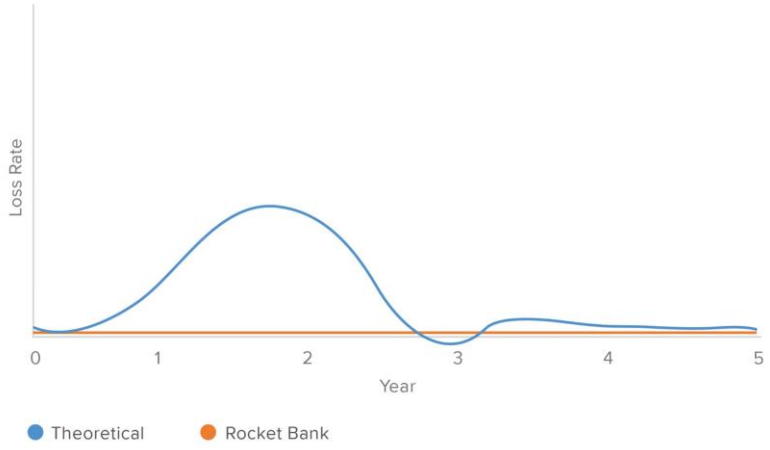


Figure 3 -- Napkin Tech Vintage Results

INITIAL ASSESSMENT: REMAINING LIFE

In a Remaining Life concept, we estimate the portfolio wind-down, and apply a per-year loss rate to that portfolio wind-down. Readers are encouraged to use our Napkin Technology (reverse of this page) to estimate the results of the Remaining Life method on this portfolio.

INITIAL ASSESSMENT: SEGMENTATION

Meaningful application of the standard requires us to balance statistical significance and granularity. It would be *intuitive* for Rocket Bank to perform separate estimations for Multifamily, Owner-Occupied, or Investment Commercial Real Estate, but it would not be *practical*. As we see above, based on a rollup to a broader "CRE" concept, Rocket Bank has a modeling problem. Whether by implementing a purely subjective framework or layering in outside experience, disaggregating into three pools would only serve to present Rocket Bank with two *more* modeling problems.

ANALYSIS AND SYNTHESIS

The predominant practice in allowance preparation under the incurred loss notion is to compute some analytical number meant to represent a historical loss rate, and then apply subjective factors on top of that number to qualitatively obtain a reserve rate the institution deems sensible; this is the practice formulated in the 2006 Interagency Policy Statement on the ALLL. When this practice is applied to institutions such as Rocket Bank, the analytical component will often produce results near to zero, requiring incredible effort and sometimes tortuous[2] arguments to obtain a result that management is comfortable with.

Core to the Practical CECL™ approach is decomposition of loss rate results into component inputs, and thinking critically about how we can justify those inputs. In the case of Rocket Bank, the 0% loss rate, whether in an incurred or lifetime notion, can be decomposed using Napkin Technology:

$$\text{Expected Loss} = \text{PD} \times \text{LGD} = 1.2\% \times 0\% = 0\%$$

Figure 4 - Expected Loss Formula in Napkin Tech

We immediately see the core problem: Rocket Bank has observed *defaults* but has no observed *losses*. Its default rate of about 1.2% is based on 300 loans in the portfolio; its loss-given-default (LGD) would then be based on **three observations**. Any number based on three observations is meaningless.

If we decide that 300 observations in a period is sufficient to determine a periodic default rate with some confidence, then we can use the 1.2% as an *analytical* input. As an alternative to subjective adjustment of the output (0%), we should use the tools available to us per the standard to build an LGD that is meaningful. We can approach this problem *analytically*, or *synthetically*.

syn·the·sis
/ˈsinTHəsəs/

noun

combination or composition, in particular.

- the combination of ideas to form a theory or system.
  noun: **synthesis**; plural noun: **syntheses**
  "the synthesis of intellect and emotion in his work"
  synonyms: combination, union, amalgam, blend, mixture, compound, fusion, composite, alloy; More
- the production of chemical compounds by reaction from simpler materials.
  noun: **synthesis**
  "the synthesis of methanol from carbon monoxide and hydrogen"

a·nal·y·sis
/əˈnaləsəs/

noun
noun: **analysis**; plural noun: **analyses**

detailed examination of the elements or structure of something, typically as a basis for discussion or interpretation.
"statistical analysis"
synonyms: examination, investigation, inspection, survey, study, scrutiny; More

- the process of separating something into its constituent elements.
  synonyms: examination, investigation, inspection, survey, study, scrutiny; More

To synthesize is to build up, and we can build an LGD assumption in any number of ways; at the least complex, we can make or borrow an assumption from elsewhere and apply it consistently (e.g. a 10% haircut in impairment analysis). We could also use an industry input for LGD, whether it was derived analytically or synthetically.

The core difference between the application of the CECL standard to community, uncomplex institutions and its application to larger, more complex institutions is that larger institutions will be able to derive

[2] But not, we hope, tortious

more of their model inputs *analytically*, using first-party data and experience. Smaller institutions, or those with no observable losses, will need to rely on more synthetic inputs, more often. Consider a *de novo* institution: it will be wholly dependent on synthetic model inputs. In the context of the incurred loss notion, larger institutions with 100+ loss events may be able to analyze losses to derive an empirical loss emergence period, while smaller institutions commonly create a credible buildup synthetically: "We get new financials every year, so we'll assume a half-year for detection; we initiate foreclosure after 180 days, and then it takes 90 days to wind through the court system and up to a year to dispose. Therefore, we assume a loss emergence period of 0.5+0.5+0.25+1=2.25 years"

We cannot guarantee that a synthetic buildup for a model input will be acceptable to any given audience, but we do strongly recommend that such approaches be boldly asserted, plausibly maintained, and consistently applied. To the simple example, above: if a 10% LGD assumption is asserted in the loss modeling effort, clear parameters should be established for when future analytical evaluation will occur, and the assumption should not be changed from period to period.

The core of the Practical CECL™ approach is to determine which inputs are best derived analytically, which are best derived synthetically, and whether first or third-party experience should be used for either.

APPLICATION: ROCKET BANK

Rather than resort entirely to qualitative adjustment, we will be applying a Net Present Value of Discounted Cash Flows model to Rocket Bank to demonstrate how thinking critically about model inputs and assumptions can produce meaningful, stable, predictable results.

Technical discussion of this measurement methodology is encompassed in the Practical CECL™ Transition Guide chapter on DCF. To compute this estimate, we require the following inputs:

INPUT	EXAMPLE	COMMENTS
Default Rate	1.3%	The most common input for an uncomplex institution to be able to derive analytically. This is a 1-year rate at which an undefaulted loan enters a state of default.
Loss Given Default	10%	If a loan defaults, this is the amount that is ultimately charged-off on the loan on a dollar basis. This is the most difficult credit input to model analytically, as the condition of default serves to dramatically curtail sample sizes. LGD is time-agnostic.
Prepayment Speed	12%	We define prepayment speed as the amount of principal collected over a period that is in addition to contract principal; this is an *explicit* input in our cashflow models. This can be derived analytically with a sufficient run of quality data, or synthetically – e.g. what input for prepayment produces a wind-down that is commensurate with the Weighted Average Life number? Prepayment is typically market-specific rather than institution-specific. We normalize prepayment inputs to 1-year numbers.
Curtailment Rate	30%	This is a statistical tendency of extended balances to be returned to the institution on non-amortizing loans.
Recovery Delay	12 months	Difficult to derive analytically; this is the time period between a default event and ultimate resolution of that default.

When we apply our cashflow projection model, each loan generates cashflows according to its contract schedule; additional cashflows are modeled for prepayment or curtailment assumptions depending on the form of the loan. Over time, portions of the extended balance are assumed to have defaulted based on the PD input, and portions of *that* balance are assumed to be recovered or lost depending on the LGD input: this implements a PDxLGDxEAD model. Defaults are continuous in our model, and the effect of lost interest are included. A contract cashflow schedule is thus transformed to an *expected* cashflow schedule; the difference between the NPV of those expected cashflows and the presented amortized cost basis of the loan is the valuation reserve for that loan. Our system calculates the effective yield to use in the discount rate at a loan level.

In short, we are applying *pool-level* credit and timing assumptions to *loan-level* cashflows to generate the shortfall in NPV that should be held as a reserve. This is a well-understood approach that is used in several accounting treatments already in journal-entry scope, such as ASC310-20 and ASC310-30 activities.

We begin our study by assuming first-party inputs are representative: 12% prepayment, 1.3% PD, and 0% LGD: this effectively models the impact of lost interest on defaulted loans. We run this both on a "pool" basis and on a "loan-level basis".

SCENARIO	RESERVE	COMMENTS
Pool Model – No LGD	0.112%	Valuation effect of lost interest on 4.5yr WAL wind-down
Loan-Level Model – No LGD	0.1099%	Valuation effect of lost interest on a bottom-up basis.

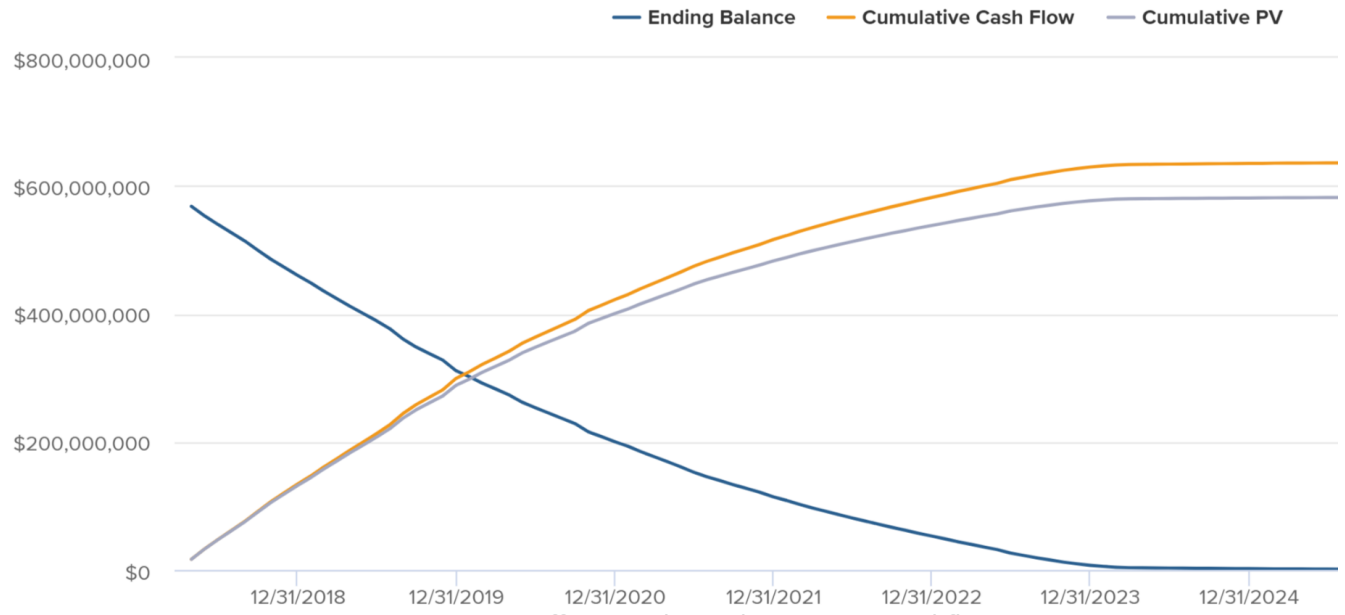


Figure 5 -- NPV Difference due to lost interest cashflows

Continuing to use loan-level projections, we now model the effect of making a 10% LGD assumption. Note that these projections still include no changes for economic forecasts, and assume a consistent credit performance through wind-down. We further contrast to a "amortization" assumption, in which we do not balloon cashflows at contract maturity; this assumption is not compliant with the standard, but useful.

SCENARIO	RESERVE	COMMENTS
Pool Model – No LGD	0.112%	Valuation effect of lost interest on 4.5yr WAL wind-down
Loan-Level Model – No LGD	0.1099%	Valuation effect of lost interest on a bottom-up basis.
Loan-Level (LL) – 10% LGD	0.376%	Including impact of lost principal on defaulted loans, simple synthetic approach. Portfolio winds down in ~5 years.
LL – 10% LGD – Renewal Assumption – With Prepayment	0.39%	This portfolio is of very long contract duration, and prepayment effects further accelerate principal; we therefore do not see a material difference in the renewal assumption. Portfolio winds down in ~6 years.
LL – 10% LGD – Renewal Assumption – No Prepayment	0.64%	Removing prepayment effects and carrying each loan to its am-through has a dramatic impact. Portfolio winds down in ~11 years.

Thus far, we have used a very simple, synthetic input for LGD (a plausible number fabricated from whole cloth) and complex modeling techniques to produce a compliant steady-state reserve of ~38bp. We have not made any adjustments for forecasted conditions.

To make these adjustments, we could rely on several techniques of varying complexity. When we perform this work for clients in exchange for commercial consideration, we use the techniques specified in our Loss Driver Analysis guide [AGM Marketing Link or sidebar.] To summarize this technique, we make some timing assumptions on the delay between default and loss, and use observable losses to back into point-in-time default rates, either using a simple or complex LGD assumption based on an institution's own experience (when available) or our proprietary database of loan-level details and losses. For institutions with observable loss history, this technique produces meaningful curves of default and relationships to economic / environmental factors; for institutions without observable loss experience, we use the guidance's prescription to use external information and layer in peer experience.

In Rocket Bank's case, using first-party loss experience produced predictably meaningless results; by layering in the experience of five specifically identified in-market peers, we produce a curve to which we can more reasonably fit expectations of loss to econometric factors.

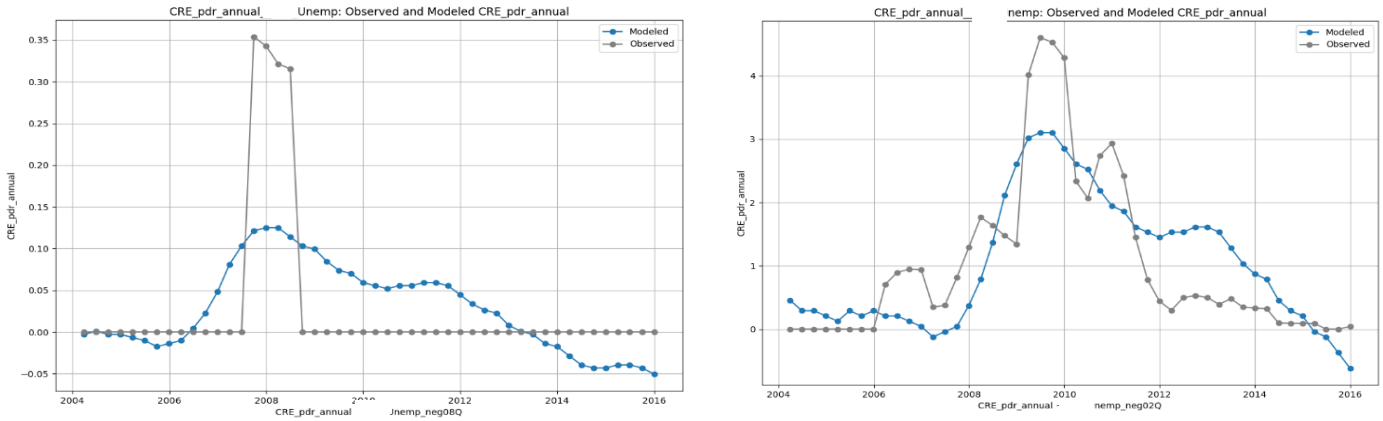


Figure 6 -- First-party (Left) and Peer-Blended (Right) default assumptions

The grey lines in the above represent default rates by application of our heuristic based on top-down losses. Note in the first-party study, we estimate approximately 0.35% at the peak, which is consistent with our ~7% LGD assumption (see below) and the above Napkin Technology estimation of a ~2.3 bp loss rate. The blue lines represent a single-factor regression's ability to describe this default experience.

By layering in peer experience, which also includes Rocket Bank's experience, we can produce a more meaningful curve (grey, right), and we can thereby apply a more meaningful regression curve (blue, right). While the selection and elimination of candidate factors are beyond the scope of this document, the critical point is that we have produced a quantifiable, defensible, intuitive, mathematical relationship between (an) environmental factor(s) e.g. regional unemployment and credit loss (default) experience. This model has several caveats – it produces a net-recovery scenario today, and under-predicts the peak and over-predicts during the recovery – but it is an important starting point:

PARAMETER	RESULT	COMMENTS
Intercept	-3.51%	Predicted default rate with 0 inputs for all factors
Intercept Confidence Interval	+/- 2%	97.5% confidence interval, on either side, for model; a quantification of the model's own precision
Coefficient – Regional Unemployment	.83	Each 1% increase in regional unemployment describes a 0.83% increase in predicted default rate. This parameter has its own confidence interval, which we will ignore in this case study.
Explanatory Power (R-Squared)	.65	On a scale of 0 to 1.0, how much of the variance in our response variable (defaults) is described by our model?

While we are well beyond the scope of Napkin Technology, we now have a justifiable model describing approximately 65% of our default rate input *at a given point in time*:

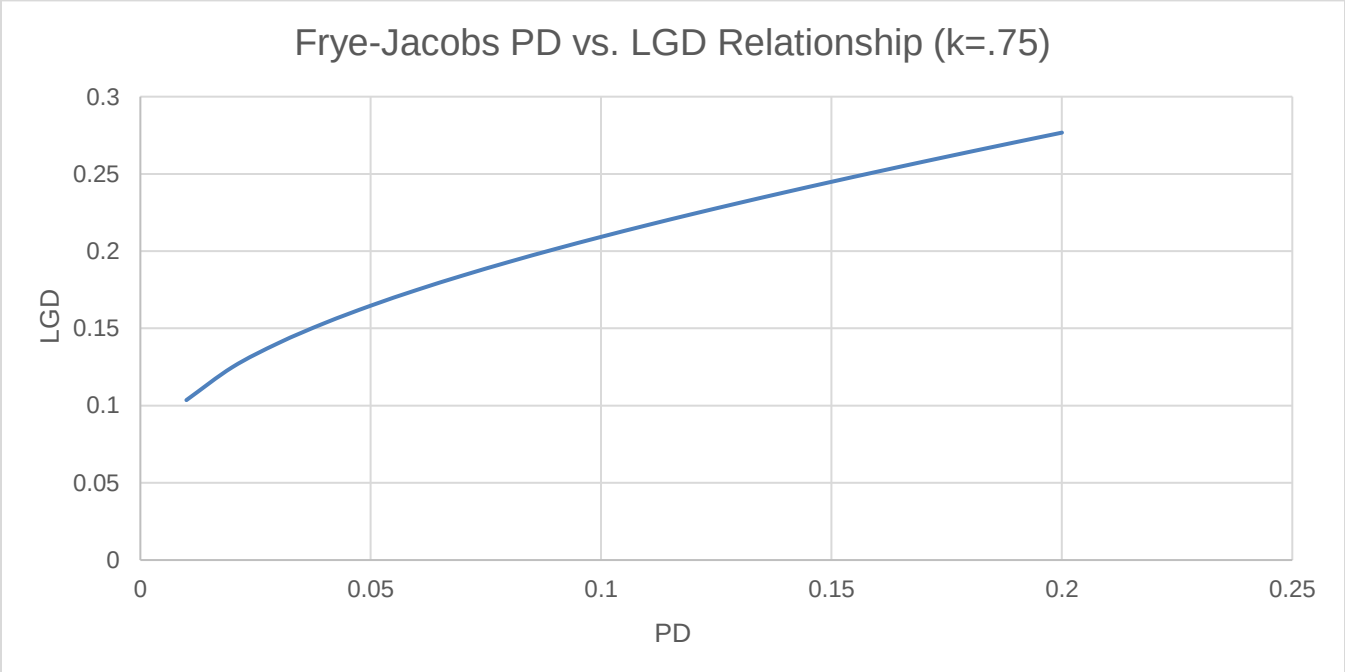
Default Rate = 0.83 x [Regional Unemployment] – 3.51% [+/- 2%]

This last term is critical; our statistical efforts are imprecise – this is the nature of a statistical exercise. The model is quantifying its own imprecision. It is management's **right** and its **responsibility** to exercise judgment in interpreting this imprecision; it is an auditor's right and responsibility to demand this judgment be consistently applied over time. Under present conditions, this formula evaluates to

Default Rate = 0.83 x 3.2 – 3.51 [+/- 2%] = -.85% +/- 2%. It would seem sensible and feasible to apply the upper end of this estimation, for a default rate of 1.15% under present conditions, especially given our *analytically derived* first-party default rate of 1.3%. In fact, we've ignored the imprecision in the coefficient factor, so let us simply anchor the intercept to the observed default rate of 1.3% -- our model becomes:

Default Rate = 0.83 x Regional Unemployment - 1.3%

The default rate is only one of the two critical credit inputs; the other is the loss-given-default. We have used the Frye-Jacobs model for relating PD to LGD in our econometric modeling; we will apply this model symmetrically in our Loss Given Default estimation. The corresponding risk index, empirically observed in our proprietary database, for CRE loans is .75, which produces a Frye-Jacobs curve as follows:

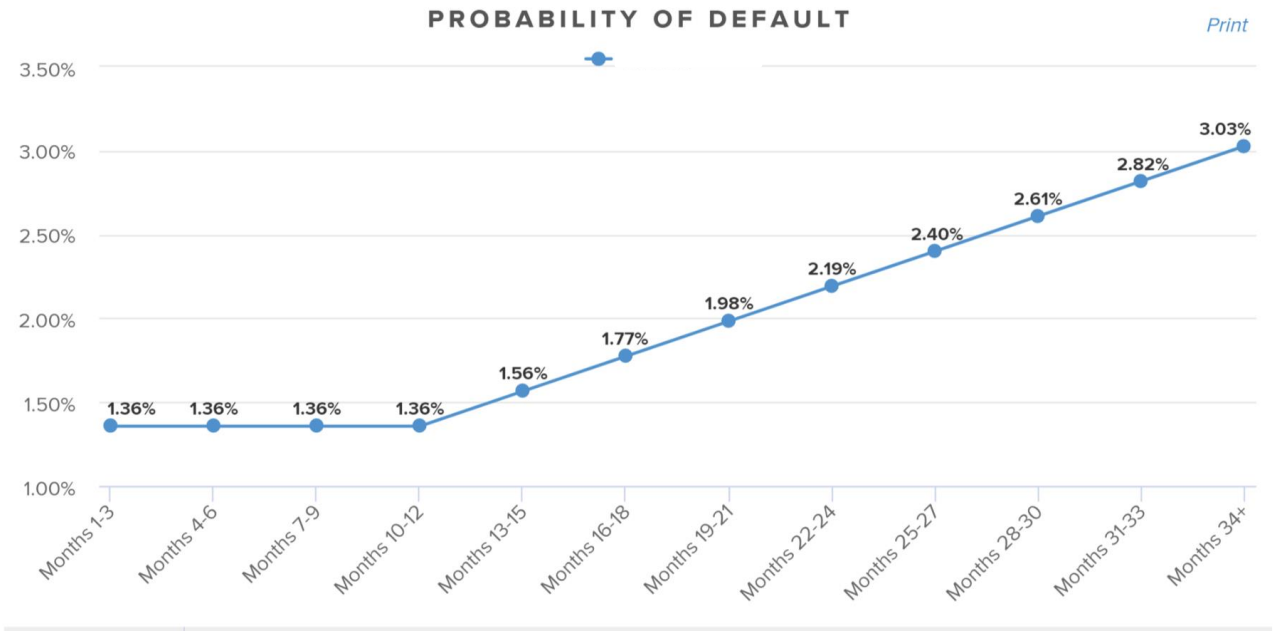


We have introduced some complexity fairly rapidly. To summarize: Rocket Bank attempted a loss-rate analysis, and calculated an observed loss rate of 0% for this pool, with a peak of 0.023% through the cycle. Recognizing its default experience was meaningful, but its loss experience was meaningless, Rocket Bank computed a model to relate environmental factors to default rates, layering experience from defensible peer institutions. Uncomfortable with assuming an LGD of 10%, Rocket Bank is using a PD ←→ LGD function derived empirically from a data set of CRE losses and defaults at a thousand institutions.

In the following scenario, Rocket Bank predicts a continuation of current conditions for one year, allowing for a 2-year reversion period of the unemployment input:

ECONOMIC FORECAST

Forecast Factor	Months 1-3	Months 4-6	Months 7-9	Months 10-12	Months 13-15	Months 16-18	Mo
Unemployment Rate in							
	3.2000%	3.2000%	3.2000%	3.2000%	3.4518%	3.7035%	
(Percent)							
Model Result	1.3560%	1.3560%	1.3560%	1.3560%	1.5650%	1.7739%	

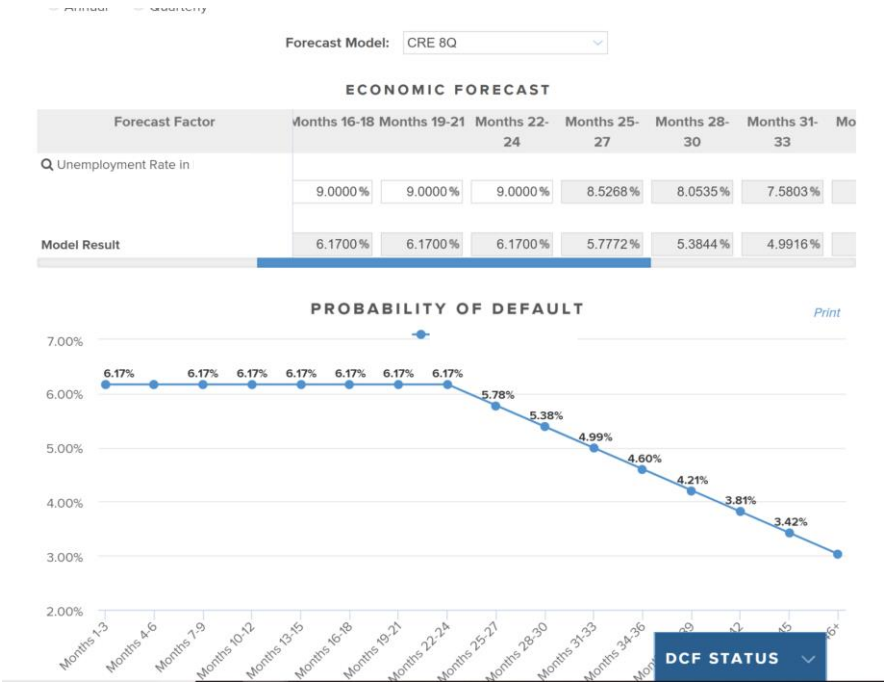


Loss given default is curved accordingly using a symmetrical application of the Frye-Jacobs PD/LGD curve.

We can also examine the impact of making a 2-year forecast of continued performing conditions; the forecast in this case will begin its reversion effects after the eighth quarter.

SCENARIO	RESULT	COMMENTS
Pool Model – No LGD	0.112%	Valuation effect of lost interest on 4.5yr WAL wind-down
Loan-Level Model – No LGD	0.1099%	Valuation effect of lost interest on a bottom-up basis.
Loan-Level (LL) – 10% LGD	0.376%	Including impact of lost principal on defaulted loans, simple synthetic approach. Portfolio winds down in ~5 years.
LL – 10% LGD – Renewal Assumption – With Prepayment	0.39%	This portfolio is of very long contract duration, and prepayment effects further accelerate principal; we therefore do not see a material difference in the renewal assumption. Portfolio winds down in ~6 years.
LL – 10% LGD – Renewal Assumption – No Prepayment	0.64%	Removing prepayment effects and carrying each loan to its am-through has a dramatic impact. Portfolio winds down in ~11 years.
LL – Forecasted 1-yr Current Conditions	0.67%	Reversion effects are always countercyclical. Compare to 2-year forecast and LL 10% LGD.
LL – Forecasted 2-yr Current Conditions	0.55%	Extension of forecast period (performing) delays countercyclical reversion effects.

Rocket Bank's forecast model allows it to hypothesize future scenarios, even if those scenarios are deemed unlikely:



SCENARIO	RESERVE	COMMENTS
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LL – Forecasted 2-yr Current Conditions	0.55%	Extension of forecast period (performing) delays countercyclical reversion effects.
LL – Forecasted 1-yr Severe	2.03%	Note countercyclical effect of shorter forecast window.
LL – Forecasted 2-yr Severe	2.29%	Extension of severe conditions increases reserve.
LL – Forecasted 2-yr Severe – Renewal Assumption – No prepayment	3.14%	Impact of retaining current book through paydown with no borrower prepayment.

QUALITATIVE ADJUSTMENT

In this analysis, we have only considered quantitative analysis of loans collectively evaluated; recall that our forecast model had an "R-squared" value, or explanatory power, of 0.65 out of 1.0. We could layer additional factors in an attempt to find a more explanatory model, but it would also stand to reason that Rocket Bank would – as a matter of policy – tolerate an additional 35% of the calculated basis for qualitative adjustment; for example, in a scenario predicting a 2% valuation reserve, qualitative adjustment could plausibly adjust this number upward or downward 70 basis points. By attempting to quantify the impact of economic and environmental future conditions on its credit experience, Rocket Bank has relegated qualitative adjustments to their intended, subjective purpose.

BREAK-EVEN ANALYSIS

Recall that Rocket Bank carries a 1.0% allocation-to-loans under the incurred loss notion. It is of interest to determine the environmental forecast required to produce this result under this more sophisticated analysis. Assuming constant liquidity inputs (prepayment), we determine that a constant default rate through wind-down of 3.05% is required to produce this valuation reserve, corresponding to a 14.25% LGD assumption. Back-solving our econometric model, this would correspond to a constant unemployment projection, over the next four and a half years, of

3.05 % = 0.83 x Regional Unemployment - 1.3% → Regional Unemployment = 5.24%

Regional economic conditions in Rocket Bank's market have not met or exceeded these conditions since 2014, and there is as of this publication date no mainstream, specific outlook that projects these conditions to obtain in the near future.

While we have demonstrated how a thoughtful buildup of model inputs can create justification for an Allowance for Credit Losses in the absence of observable loss experience, this number (0.6%) is just over half of the current reserve established (for all portfolios) at Rocket Bank. It is important for all audiences to understand that a more sophisticated approach to modeling may produce results that are *lower* under a Current Expected notion than under an Incurred notion, especially given mainstream present-day outlooks. If modeling improvements implemented as a result of the new accounting standard cause material downward changes in the stated position for the Allowance, this does not signal that legacy models are *wrong*. Indeed, fundamental conceptual changes in modeling approach may make it impossible to reconcile the two figures.

SUMMARY AND CONCLUSIONS

By decomposing our model inputs and thoughtfully applying input buildup both analytically and synthetically – using internal and external information where appropriate –we strongly justify a level of allocation that would require **purely** subjective buildup under a loss-rate approach. Rocket Bank's policies and procedures for collective analysis are well-considered, stable in stable conditions, and predictably responsive to changing conditions.

While individual evaluation and qualitative adjustment will still be important considerations to Rocket Bank, they will not be the sole drivers of allocation under this policy.

Though Rocket Bank is an uncomplex community institution, this approach is not "simple". It is, however, *practical*. Major model assumptions will be self-backtesting due to point-in-time model projections. If and when credit loss *is* recognized, it will have been predicted by the model, and the model will not be volatile in response. The model will be automatically sensitive to changes in loan-level parameters (rates and durations) and pool-level behavior (prepayment speed), and such changes will be specifically attributable in rollforward reporting.

Regardless of institutional complexity, we recommend entities first evaluate modeling approaches using Napkin Technology and top down data; while not a compliant method of financial statement preparation, this approach will be quickly directive in terms of the relative benefits of additional data gathering, model implementation, etc. When Napkin Technology produces a *prima facie* meaningless result, consider decomposing your model into its constituent inputs and how you might apply an analytical or synthetic buildup to those inputs.

ABOUT THE AUTHOR

More roll-rate modeler than role-model, Garver Moore joined Sageworks in 2015 to bring his experience leading capital technology and analytics projects to bear on the impending CECL transition challenge. He is the first known human being to apply the cumulative / open-pool loss rate approach to an actual – not notional – community financial institution, work for which he was awarded the Presidential Medal of Freedom in a secret, undocumented ceremony. This first CECL-compliant collective analysis result (twenty basis points) inspired him to develop the Practical CECL™ Transition approach, and he is the lead author of the accompanying Transition Guide. Serving as Managing Director of the Sageworks Advisory Services group, he leads our CECL Transition and research/analytics practices.

Prior to joining Sageworks, Garver worked with C-suite executives on strategic projects at Accenture and later as Managing Partner of the Orange Advisory Group. He holds a degree in Computer Engineering from Duke University, but prefers people to processors.