



WILARY WINN LLC

ADVICE TO
STRENGTHEN
FINANCIAL
INSTITUTIONS

FDIC Training: CECL & Liquidity

October 2024

10/8/2024

AGENDA

- **Introduction to Wilary Winn**
- **Purpose of the Presentation**
- **Regulatory Context for CECL**
- **Available CECL Models**
- **Relevant Definitions**
- **WARM vs. DCF Comparison**
- **Industry Insights by Loan Type**
- **Key CECL Takeaways**
- **Liquidity**
- **Conclusion & Q&A**



INTRODUCTION TO WILARY WINN

Who We Are

Founded in 2003 and located in Oakdale, Minnesota, our mission is to strengthen community financial institutions.

Who We Serve

We serve community financial institutions located across the country, including:

- Over 300 community banks, including 73 that are publicly traded.
- Nearly 300 credit unions, including 41 of the top 100.



WILARY WINN LLC

TODAY'S PRESENTERS



Douglas M. Winn
President and Co-founder

Nearly 40 years of executive level financial experience.
Nationally recognized expert regarding accounting and regulatory reporting for financial institutions.



Frank J. Wilary
Principal and Co-founder

Over 25 years of diversified experience in the financial services industry.
Areas of expertise include asset liability management (ALM), credit loss modeling, capital markets, structured finance, derivatives and information systems.



Michael Tessier
Director

Over 8 years serving financial institutions.
Focused on advisory designed to strengthen financial institutions.



WILARY WINN LLC

PURPOSE OF TODAY'S PRESENTATION

- **Provide Regulatory Insights on CECL**
- **Compare CECL Models with a Focus on DCF**
- **Discuss Liquidity Risk Management in a Regulatory Context**
- **Equip Examiners with Actionable Guidance**



REGULATORY CONTEXT FOR CECL

- **Why was CECL implemented?**
 - Response to the **2008 financial crisis**
 - Forward looking estimates
 - **Goal:** timely recognition of expected credit losses
- **Key Features of CECL**
 - Allowance for Credit Losses
 - Broad Application
- **Regulatory Guidance Highlights (FDIC):**
 - Institutions must use a **broader range of data** to estimate lifetime credit losses
 - Estimation approaches that build on **existing credit risk management systems**
 - CECL is **scalable** to institutions of all sizes



AVAILABLE CECL MODELS

Overview of CECL Models

1. Snapshot
2. Vintage
3. Migration
4. Probability of Default & Loss Given Default (PD/LGD)
5. Weighted Average Remaining Maturity (WARM)
6. Discounted Cash Flow (DCF)



AVAILABLE CECL MODELS

Snapshot Model

- Groups loans or financial assets with similar risk characteristics into pools.
- Typically used for homogeneous loan groups.
- Expected credit losses are calculated by analyzing the pool's historical performance.
- One of the simplest methodologies.
- Requires significant analysis to support qualitative factors.

CECL Example: Snapshot Methodology			
Year End	Amortized Cost	Net COs From 2018 Snapshot Balance	Calculation
2019	100,000,000	-	A
2020	92,049,543	150,000	B
2021	83,701,562	260,000	C
2022	74,936,183	270,000	D
2023	65,732,534	50,000	E
2024	56,068,704	-	F
2019 Pool's Cumulative Net COs		730,000	G = SUM (A : F)
2019 Amortized Cost		100,000,000	A
Unadjusted Net CO Rate		0.73%	H = G / A
Qualitative Adjustments		0.25%	I
Total ACL % for 2024		0.98%	J = H + I
2024 Amortized Cost		56,068,704	F
Total ACL \$ for 2024		549,473	L = J x F



AVAILABLE CECL MODELS

Vintage Model

- The **Vintage Model** tracks credit losses based on the origination date (or "vintage") of the loans.
- Credit losses are estimated based on the historical performance of each vintage cohort.
- Provides insights into how different economic cycles or underwriting standards impact losses over time.

CECL Example: Vintage Methodology								
Origination		Net Charge-Offs					Remaining	Remaining
Vintage	Amount	Year 1	Year 2	Year 3	Year 4	Year 5	Lifetime Net Charge-Offs (%)	Lifetime Net Charge-Offs (\$)
2019	22,000,000	0.03%	0.42%	0.24%	0.12%	0.03%	n/a	n/a
2020	19,000,000	0.03%	0.69%	0.30%	0.18%	0.03%	0.03%	5,700
2021	15,000,000	0.01%	0.24%	0.12%	0.15%	0.03%	0.18%	27,000
2022	17,000,000	0.02%	0.30%	0.22%	0.15%	0.03%	0.40%	68,000
2023	14,000,000	0.01%	0.41%	0.22%	0.15%	0.03%	0.81%	113,750
2024	13,000,000	0.02%	0.41%	0.22%	0.15%	0.03%	0.83%	108,277

Unadjusted Net Charge-Offs (\$)	322,727
2024 Amortized Cost	56,068,704
Unadjusted Net Charge-Offs (%)	0.58%
Qualitative Adjustments	0.25%
Total ACL % for 2024	0.83%
Total ACL \$ for 2024	462,899



AVAILABLE CECL MODELS

Migration Model

- The **Migration Model** tracks the movement of loans between credit risk categories (e.g., risk ratings).
- Focuses on credit quality changes.
- Migration patterns combined with forward-looking forecasts.

CECL Example: Migration Methodology					
Risk Rating	2019 Balance	Pool Losses	Loss Rate	2024 Balance	Expected Losses
1	-	-	0.00%	-	-
2	8,000,000	-	0.00%	12,000,000	-
3	35,000,000	15,000	0.04%	36,000,000	15,429
4	25,000,000	62,000	0.25%	28,800,000	71,424
5	15,000,000	78,000	0.52%	21,600,000	112,320
6	12,000,000	500,000	4.17%	18,000,000	750,000
7	5,000,000	1,200,000	24.00%	3,600,000	864,000
8	-	-	0.00%	-	-
Totals	100,000,000	1,855,000	1.86%	120,000,000	1,813,173
Unadjusted 2024 ACL %					1.51%
Qualitative Adjustments					0.05%
Total ACL % for 2024					1.56%
Total ACL \$ for 2024					1,873,173



AVAILABLE CECL MODELS

Probability of Default & Loss Given Default (PD/LGD) Model

- The **PD/LGD Model** estimates credit losses by calculating two key components:
 1. Probability of Default (PD)
 2. Loss Given Default (LGD)
- PD is typically estimated using historical data.
- LGD is calculated using historical recovery rates in the event of default.

CECL Example: PD/LGD Methodology					
Year	Average Loans	Net Charge-Off	Non-Performing Assets	Probability of Default	Loss Given Default
	A	B	C	$D = C / A$	$E = B / C$
2014	104,000,000	80,000	2,000,000	1.92%	4.00%
2015	100,000,000	440,000	3,000,000	3.00%	14.67%
2016	106,000,000	290,000	2,000,000	1.89%	14.50%
2017	105,000,000	380,000	1,000,000	0.95%	38.00%
2018	103,000,000	160,000	500,000	0.49%	32.00%
2019	107,000,000	230,000	2,000,000	1.87%	11.50%
2020	130,000,000	440,000	1,000,000	0.77%	44.00%
2021	119,000,000	580,000	4,000,000	3.36%	14.50%
2022	128,000,000	420,000	1,000,000	0.78%	42.00%
2023	130,000,000	170,000	700,000	0.54%	24.29%

10-Year Median:		
Probability of Default (PD)	1.41%	$F = \text{MEDIAN}(D)$
Loss Given Default (LGD)	19.48%	$G = \text{MEDIAN}(E)$
Unadjusted 2024 ACL %	0.27%	$H = F \times G$
Qualitative Adjustments	0.25%	I
Total ACL % for 2024	0.52%	$J = H + I$
Current Balance	125,000,000	K
Total ACL \$ for 2024	655,955	$L = J \times K$



AVAILABLE CECL MODELS

Weighted Average Remaining Maturity (WARM) Model

- The **WARM Model** estimates expected credit losses based on the weighted average remaining maturity.
- Applies historical loss rates to project future losses over the remaining life.
- The WARM model calculates a pool's weighted average remaining maturity based on contractual attributes, adjusted for prepayment assumptions.

CECL Example: WARM Methodology					
Loan Category	2024 Balance	Annual Loss Rate %	Wtd. Avg. Remaining Maturity	CECL Amount	CECL Percent
Calculation Steps	A	B	C	D=AxBxC	E=D/A
Credit Card	135,000,000	0.86%	2.75	3,198,690	2.37%
Auto Loan	180,000,000	0.52%	1.88	1,746,144	0.97%
Auto Lease	90,000,000	0.59%	1.75	926,100	1.03%
1-4 Family (1st)	270,000,000	0.02%	4.91	318,163	0.12%
1-4 Family (Jr)	162,000,000	0.03%	3.22	175,240	0.11%
Home Equity	81,000,000	0.03%	3.45	80,482	0.10%
CRE - Owner Occ	216,000,000	0.49%	5.24	5,568,653	2.58%
CRE - Non Owner Occ	234,000,000	0.56%	5.12	6,728,417	2.88%
Total	1,368,000,000	0.35%	3.89	18,741,889	1.37%



AVAILABLE CECL MODELS

Discounted Cash Flow (DCF) Model

- The **Discounted Cash Flow (DCF) Model** estimates expected credit losses by projecting the future cash flows.
- The DCF model forecasts expected cash flows (including principal and interest payments) based on current conditions and reasonable and supportable forecasts.
- The difference between the amortized cost and the discounted cash flows represents the expected credit loss.

Why It Is Superior:

The DCF model is considered highly reliable because it:

- Incorporates forward-looking information.
- Considers the time value of money.
- Works well for complex portfolios and assets with variable cash flows.
- Ensures a comprehensive view of credit risk by integrating multiple factors.



AVAILABLE CECL MODELS

Discounted Cash Flow (DCF) Model (cont.)

CECL Example: DCF Methodology															
Projection Year	Performing Balance	New Defaults	In Foreclosure	Amortization Factor	Expected Amortization	Voluntary Prepayments	Amortization From Defaults	Actual Amortization	Expected Interest	Interest Lost	Actual Interest	Principal Recovery	Principal Loss	Amortized Default Balance In Recovery Monrh	Loan Cash Flows
2023	100,000,000			1.0000											
2024	77,485,264	896,973	5,863,693	0.9209	7,344,486	14,314,431	41,155	7,303,332	4,485,139	24,604	4,460,535	-	-	-	26,078,298
2025	59,310,612	691,479	8,921,980	0.8378	6,529,678	11,023,877	70,382	6,459,296	3,479,533	40,892	3,438,640	642,440	179,395	821,835	21,564,254
2026	44,698,778	525,886	6,776,655	0.7504	5,775,053	8,373,142	62,248	5,712,805	2,646,267	31,100	2,615,167	486,729	138,296	625,025	17,187,843
2027	33,006,054	393,021	5,055,995	0.6586	5,107,639	6,247,118	55,054	5,052,585	1,977,685	23,242	1,954,443	361,935	105,177	467,112	13,616,081
2028	23,699,916	286,945	3,682,890	0.5620	4,517,356	4,550,528	48,692	4,468,665	1,443,910	16,969	1,426,941	262,435	78,604	341,039	10,708,569
2029	16,340,339	202,749	2,593,587	0.4606	3,995,292	3,204,600	43,064	3,952,228	1,020,234	11,990	1,008,244	183,581	57,389	240,970	8,348,654
2030	10,564,198	136,378	1,735,442	0.3539	3,533,562	2,144,289	38,087	3,495,475	686,255	8,065	678,190	121,538	40,550	162,087	6,439,491
2031	6,072,247	84,488	1,065,044	0.2418	3,125,194	1,315,954	33,686	3,091,508	425,146	4,996	420,150	73,140	27,276	100,416	4,900,752
2032	2,618,266	44,326	546,646	0.1239	2,764,020	675,429	29,793	2,734,227	223,049	2,621	220,428	35,785	16,898	52,682	3,665,868
2033	-	-	99,814	-	2,444,071	186,917	12,723	2,431,348	68,564	536	68,027	7,762	8,434	16,196	2,694,055

Time To Liquidation	12 Months
Conditional Repayment Rate	15.00%
Conditional Default Rate	1.00%
Loss Severity	20.00%

Loan Rate	5.00%
Net Present Value of Cash Flows	96,976,129
Amortized Cost	100,000,000
CECL Amount	3,023,871



RELEVANT DEFINITIONS

Probability of Default (PD): The likelihood that a borrower will default on a loan within a given time period, typically expressed as a percentage.

Loss Given Default (LGD): The percentage of the loan balance that is expected to be lost if the borrower defaults, after considering recoveries such as collateral or guarantees.

Exposure at Default (EAD): The total outstanding balance or amount at risk at the time of default, including both principal and accrued interest.

Conditional Repayment Rate (CRR): Annual amount of expected voluntary payoffs as a percentage of the principal amount outstanding at the beginning of the year.

Conditional Default Rate (CDR): Annual amount of expected defaults as a percentage of the principal amount outstanding at the beginning of the year.

Conditional Prepayment Rate (CPR): Annual percentage of expected voluntary and involuntary payoffs (defaults). $CRR\% + CDR\% = CPR\%$.

Loss Severity: Loss Severity expected on a loan that does go into default. This is equal to the liquidated Principal Balance minus any recovered amount divided by the Principal Balance. Severity % is the inverse of a recovery rate. Synonymous with LGD.



WARM vs. DCF COMPARISON

WARM vs. DCF Comparison		
Aspect	WARM Model	DCF Mode
Methodology	Applies historical loss rates over the remaining life of the loan pool.	Projects future cash flows and discounts them to present value to estimate credit losses.
Macroeconomic Considerations	Limited integration of forward-looking data; relies heavily on historical loss rates.	Fully integrates past events, current conditions, and forward-looking macroeconomic forecasts.
Credit Loss Calculation	Combines probability of default and loss severity in a single aggregate loss rate.	Models default probability and loss severity separately, enhancing accuracy and granularity.
Data Granularity	Uses broad categories, aggregating loans with different terms, credit scores, and LTVs.	Analyzes loans individually or in detailed cohorts, incorporating updated borrower credit and collateral data.
Model Complexity	Simple and retrospective; focuses on historical loss rates applied to weighted average maturities.	Prospective and dynamic, incorporating detailed loan-level attributes and changing conditions.
Prepayments	Prepayments are often misestimated based on historical data, leading to inaccuracies.	Prepayments are modeled directly based on borrower incentives, market interest rates, and updated loan information.
Use Cases	Primarily for estimating reserves in a straightforward manner; lacks versatility.	Can be used for multiple purposes beyond reserve estimation, including ALM, stress testing, and loan pricing.
Adjustments	Requires significant qualitative and environmental adjustments to account for model limitations.	Typically requires fewer adjustments due to its granularity and incorporation of current and forecasted conditions.
Predictive Power	Less predictive, especially during economic stress, due to reliance on retrospective data.	Highly predictive, adjusting dynamically to changes in borrower creditworthiness and economic forecasts.



WARM vs. DCF COMPARISON (cont.)

Some of the most important elements within the CECL framework are the:

1. Need to include macroeconomic considerations.
2. Requirement to use relevant forward-looking information.
3. Requirement that if outside of industrywide data is used, it must be relevant and reliable.
4. Life-of-loan calculations and need to consider prepayments.



WARM vs. DCF COMPARISON (cont.)

- Most models, including WARM, are based on the total loss rate.
- Loss rates are not linear.
- In practice, this means that the more granular the model, the more predictive it is.
- Credit scores migrate over time, and collateral values change as well.

Loan Amount	FICO	LTV	CDR	Severity	CECL Reserve (\$)	CECL Reserve (%)
250,000	850	60%	0.016%	10.000%	50	0.020%
250,000	750	100%	0.072%	15.326%	337	0.135%
250,000	650	90%	0.764%	12.384%	3,192	1.277%
250,000	550	70%	3.856%	10.000%	12,780	5.112%
250,000	450	80%	6.980%	11.629%	21,669	8.667%
1,250,000	650	80%	2.338%	11.868%	38,027	3.042%

Loan Amount	FICO	LTV	CDR	Severity	CECL Reserve (\$)	CECL Reserve (%)
250,000	650	80%	0.704%	11.283%	2,767	1.107%
250,000	650	80%	0.704%	11.283%	2,767	1.107%
250,000	650	80%	0.704%	11.283%	2,767	1.107%
250,000	650	80%	0.704%	11.283%	2,767	1.107%
250,000	650	80%	0.704%	11.283%	2,767	1.107%
1,250,000	650	80%	0.704%	11.283%	13,833	1.107%



WARM vs. DCF COMPARISON (cont.)

WARM Method

Using our multi-billion-dollar, multi-year dataset, the following examples show how a WARM model would have performed in the great financial crisis and the years after.

WARM Method %					WARM Method \$				
Year	Beginning Reserve	Chargeoffs	Provision Expense	Ending Reserve	Year	Beginning Reserve	Chargeoffs	Provision Expense	Ending Reserve
2009	0.14%	0.94%	2.80%	2.01%	2009	723,701	4,680,674	14,021,839	10,064,866
2010	2.01%	0.95%	2.19%	3.25%	2010	10,064,866	4,737,628	10,930,094	16,257,333
2011	3.25%	1.13%	2.25%	4.37%	2011	16,257,333	5,651,152	11,263,524	21,869,706
2012	4.37%	0.76%	0.03%	3.65%	2012	21,869,706	3,783,483	160,951	18,247,174
2013	3.65%	0.31%	1.23%	4.57%	2013	18,247,174	1,562,865	6,164,640	22,848,949
2014	4.57%	0.11%	-1.98%	2.48%	2014	22,848,949	534,196	(9,901,772)	12,412,981
2015	2.48%	0.04%	-1.49%	0.95%	2015	12,412,981	219,601	(7,455,887)	4,737,494
2016	0.95%	0.00%	-0.63%	0.31%	2016	4,737,494	6,074	(3,174,353)	1,557,067
2017	0.31%	0.01%	-0.18%	0.12%	2017	1,557,067	45,723	(919,582)	591,763
2018	0.12%	0.04%	0.04%	0.12%	2018	591,763	216,773	214,570	589,560
2019	0.12%	0.01%	0.01%	0.11%	2019	589,560	71,727	56,292	574,124
2020	0.11%	0.01%	-0.01%	0.09%	2020	574,124	64,983	(65,099)	444,042
2021	0.09%	0.00%	-0.03%	0.06%	2021	444,042	16,287	(144,376)	283,379
2022	0.06%	0.00%	0.00%	0.05%	2022	283,379	23,542	(18,287)	241,550



WARM vs. DCF COMPARISON (cont.)

DCF Method

We also show how the Wilary Winn DCF models actually performed over the same time frame.

DCF Method %				
Year	Beginning Reserve	Chargeoffs	Provision Expense	Ending Reserve
2009	0.39%	0.94%	5.30%	4.75%
2010	4.75%	0.95%	0.78%	4.59%
2011	4.59%	1.13%	2.03%	5.49%
2012	5.49%	0.76%	0.34%	5.07%
2013	5.07%	0.31%	2.02%	6.78%
2014	6.78%	0.11%	-5.09%	1.58%
2015	1.58%	0.04%	-0.83%	0.71%
2016	0.71%	0.00%	-0.21%	0.50%
2017	0.50%	0.01%	-0.08%	0.41%
2018	0.41%	0.04%	-0.06%	0.31%
2019	0.31%	0.01%	-0.10%	0.20%
2020	0.20%	0.01%	-0.06%	0.13%
2021	0.13%	0.00%	0.12%	0.25%
2022	0.25%	0.00%	-0.02%	0.22%

DCF Method \$				
Year	Beginning Reserve	Chargeoffs	Provision Expense	Ending Reserve
2009	1,948,997	4,680,674	26,499,608	23,767,931
2010	23,767,931	4,737,628	3,922,581	22,952,883
2011	22,952,883	5,651,152	10,149,225	27,450,957
2012	27,450,957	3,783,483	1,704,937	25,372,411
2013	25,372,411	1,562,865	10,084,313	33,893,859
2014	33,893,859	534,196	(25,453,290)	7,906,373
2015	7,906,373	219,601	(4,135,910)	3,550,862
2016	3,550,862	6,074	(1,036,389)	2,508,399
2017	2,508,399	45,723	(417,957)	2,044,719
2018	2,044,719	216,773	(275,020)	1,552,927
2019	1,552,927	71,727	(485,466)	995,733
2020	995,733	64,983	(291,713)	639,037
2021	639,037	16,287	613,402	1,236,153
2022	1,236,153	23,542	(88,284)	1,124,327



WARM vs. DCF COMPARISON (cont.)

- Net provision expense totals approximately \$21 million over the 14-year period.
- The WARM method grossly understates the required reserve in 2009 and does not release enough reserve in 2014.

Year	WARM Method		DCF Method	
	Provision Expense	Ending Reserve	Provision Expense	Ending Reserve
2009	14,021,839	10,064,866	26,499,608	23,767,931
2010	10,930,094	16,257,333	3,922,581	22,952,883
2011	11,263,524	21,869,706	10,149,225	27,450,957
2012	160,951	18,247,174	1,704,937	25,372,411
2013	6,164,640	22,848,949	10,084,313	33,893,859
2014	(9,901,772)	12,412,981	(25,453,290)	7,906,373
2015	(7,455,887)	4,737,494	(4,135,910)	3,550,862
2016	(3,174,353)	1,557,067	(1,036,389)	2,508,399
2017	(919,582)	591,763	(417,957)	2,044,719
2018	214,570	589,560	(275,020)	1,552,927
2019	56,292	574,124	(485,466)	995,733
2020	(65,099)	444,042	(291,713)	639,037
2021	(144,376)	283,379	613,402	1,236,153
2022	(18,287)	241,550	(88,284)	1,124,327
Total	21,132,556		20,790,037	



WARM vs. DCF COMPARISON (cont.)

Why DCF is More Reliable

Granularity and Predictive Accuracy:

The DCF model estimates credit losses at the loan level or detailed cohort level, using updated borrower credit scores and collateral values, offering greater predictive power than aggregate methods like WARM.

Prospective vs. Retrospective:

DCF incorporates current and forward-looking data—including prepayments, defaults, and macroeconomic conditions—resulting in a more dynamic and reliable estimation of losses.

Transparency and Versatility:

The DCF model is transparent, leveraging well-documented financial mathematics, and can be used for multiple business purposes, including stress testing, asset-liability management (ALM), and strategic decision-making.



WARM vs. DCF COMPARISON (cont.)

Other Benefits of DCF

- **Net Economic Value (“NEV”) for ALM models.**

More importantly, credit, interest rate, and liquidity risks can be and should be measured on an integrated basis.

- **Stress Testing**

Financial institutions can run multiple iterations of adverse macroeconomic circumstances and quantify the capital they have at risk.

- **Loan Pricing Optimization**

The same iterations can be run to set all-in loan pricing to ensure the interest rate is sufficient to cover expected credit losses under adverse scenarios.

- **Strategic Adjustments and Cross-Departmental Communication**

Changes to lending strategies can be easily communicated because the same primary variables used in the model – credit score and LTV – are the same ones used to make new loans.



Model Validation & Interagency Guidance

- **Supervisory Guidance on Model Risk Management:** Issued by the Federal Reserve and OCC, it emphasizes the importance of model validation for mitigating model risk and ensuring models are performing as intended. Key focuses include model development, implementation, and ongoing monitoring.
- **Gold Standard Approach to Model Validation:**
 - Thorough review of model documentation
 - Full evaluation of model assumptions
 - Data quality assessment
 - Independent replication
 - Sensitivity and stress testing
 - Benchmarking and back-testing



SAB 119 & AICPA CECL Practice Aid

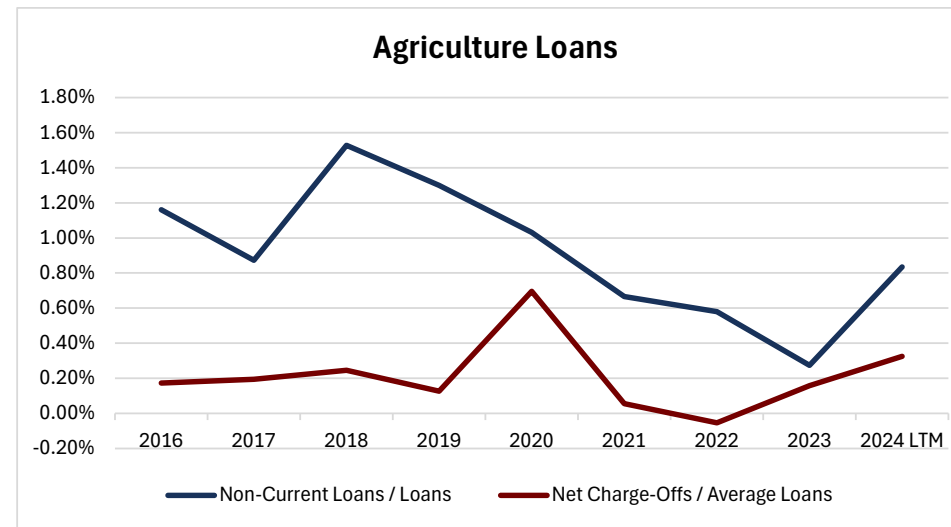
- **Staff Accounting Bulletin No. 119:** Provides updated guidance on measuring current expected credit losses (CECL) under ASC Topic 326, focusing on systematic methodologies and the necessary documentation for allowance estimates. Emphasizes governance and internal control considerations.
- **AICPA CECL Practice Aid:** Offers audit considerations for CECL, focusing on internal controls, data reliability, model assumptions, and audit committee oversight.



INDUSTRY INSIGHTS BY LOAN TYPE

Agricultural Loans

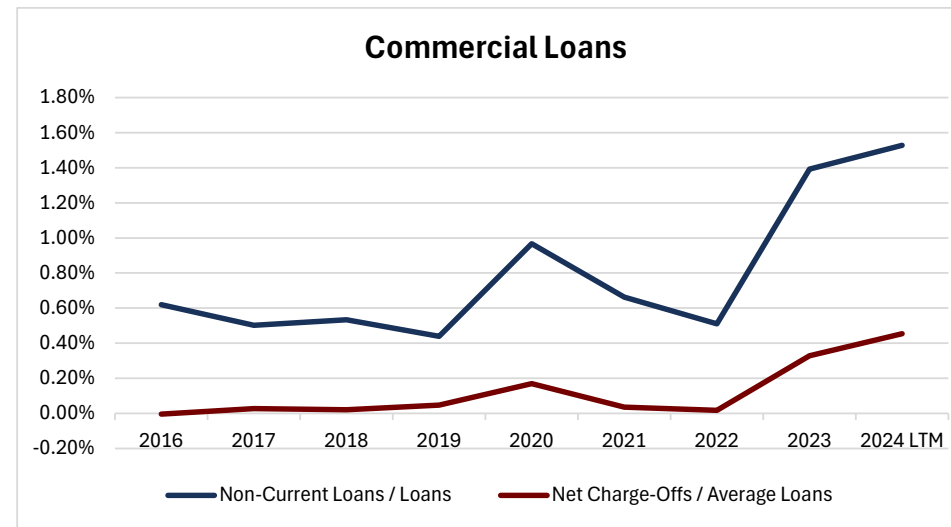
- **Unique Risk Profile**
 - Seasonal cash flow variability
 - Commodity prices
 - Weather conditions
 - Government policies
- **Collateral Valuation Challenges**
- **Geographic Sensitivity**



INDUSTRY INSIGHTS BY LOAN TYPE

Commercial Loans

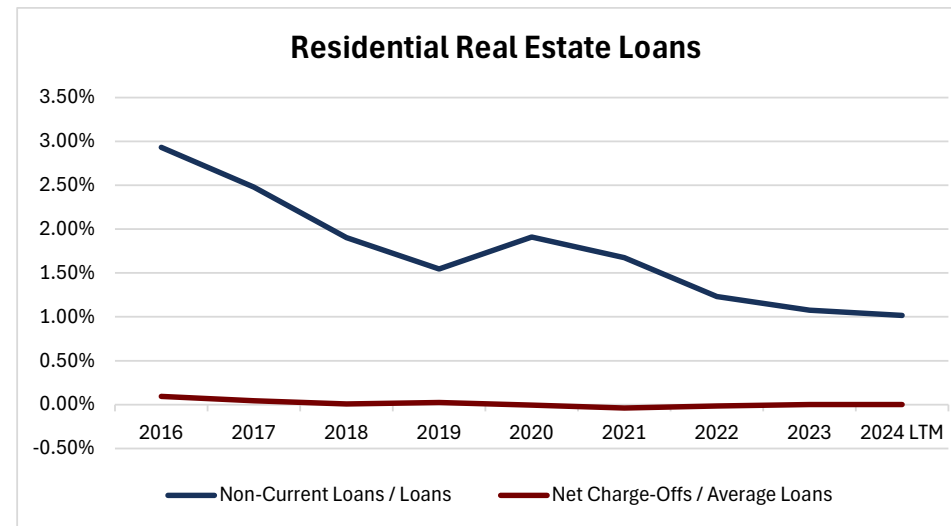
- **Borrower Credit Quality**
- **Industry-Specific Risks:**
 - Retail
 - Hospitality
 - Office
 - Manufacturing
- **Collateral and Guarantees**
- **Loan Structuring:**
 - Balloon payments
 - Variable interest rates
 - Lines of credit



INDUSTRY INSIGHTS BY LOAN TYPE

Residential Real Estate Loans

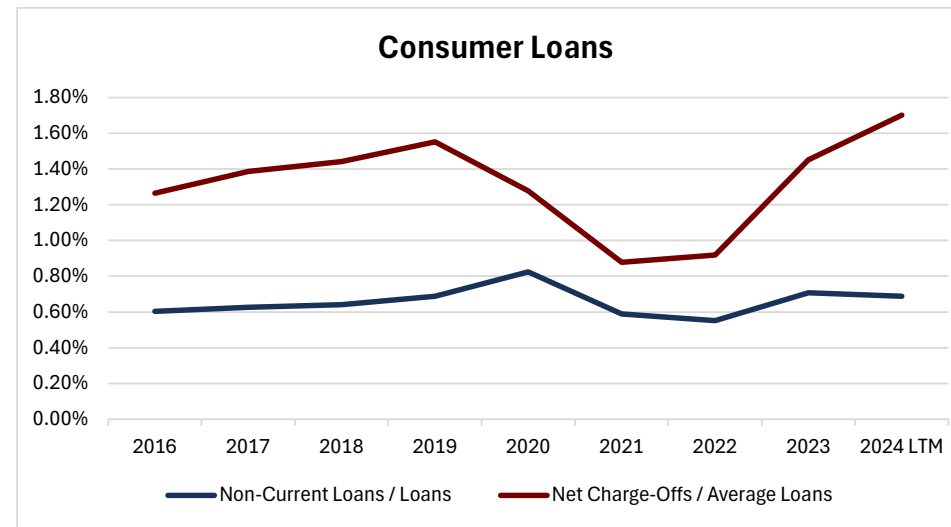
- **Housing Market Sensitivity**
- **Creditworthiness of Borrowers:**
 - Credit scores (FICO)
 - Loan-to-value ratios (LTV)
- **Prepayments**
- **Market Volatility**



INDUSTRY INSIGHTS BY LOAN TYPE

Consumer Loans

- **Shorter Loan Terms**
- **Credit Risk Variability**
- **Unsecured Nature**
- **Macroeconomic Sensitivity**



KEY CECL TAKEAWAYS

- Forward-Looking Approach
- Granularity Enhances Accuracy
- Model Choice Matters
- Importance of Credit and Collateral Data
- Adjustments for Macroeconomic Conditions
- Limitations of Retrospective Models



LIQUIDITY

Liquidity Background

Liquidity

Financial institution's capacity to meet its cash and collateral obligations at a reasonable cost

Liquidity Risk

Risk that a financial institution's condition is threatened to do its inability to meet its obligations

Liquidity Management

Process of estimating and stress testing a financial institution's cash flow needs and ensuring sufficient funds are available to meet all obligations

Liquidity Ratios

Financial metrics used to assess a financial institution's ability to meet its obligations



LIQUIDITY

Liquidity Responsibilities

Liquidity Objective

Identify, measure, monitor and control the funding and liquidity risk

Board of Directors

Ultimately responsible for the liquidity risk assumed by the institution. Ensures that the liquidity risk tolerance is clearly communicated and that the trade-off between liquidity and short-term profits is understood.

Senior Management

Responsible for ensuring that board-approved policies are appropriately executed and that liquidity risk is controlled

Asset Liability Committee

Actively monitor the institution's liquidity profile



LIQUIDITY

Large Bank Failures in 2023 Due to Lack of Liquidity

Silicon Valley Bank

Provided financing to the venture-backed tech sector

Closed on March 10, 2023

Signature Bank

Served specialty businesses including crypto currency

Closed on March 12, 2023

First Republic Bank

Catered to high-net worth individuals

Closed on May 1, 2023



LIQUIDITY

Large Bank Failures in 2023 Characteristics

- **Large Concentrations of Uninsured Deposits**
- **Low Yielding Investment Portfolio with Long Duration**
Sale of securities would result in significant realized losses
- **Limited Loyalty of Customers**
- **Lack of scenario analysis, planning and contingent funding**
- **Classic Bank Run**



LIQUIDITY

Potential Liquidity Deficiencies

- **Insufficient Amounts of Liquid Assets**
Not enough cash or short-term securities
- **Volatile Short-term Liabilities Funding Risky Assets**
Duration mismatch and changing market conditions
- **Inability to Accurately Project Cash Flows**
Need to understand the nature of the liquidity risks and cover both expected needs and unexpected deviations
- **Insufficient or Untested Contingent Liquidity Plans**
Importance of diversified sources and operational efficiency to pledge assets



LIQUIDITY

Recommendations

- **Non-maturity Deposit Studies**
Understand customer behavior and surge deposits as interest rates change
- **Use of Early Warning Indicators**
- **Liquidity Buffer to Detailed and Frequent Liquidity Stress Tests**
- **Diversification of Funding Sources within Contingency Funding Plan**



LIQUIDITY

Guidance

- **Liquidity Risk Management Standards**
Liquidity coverage ratio and net stable funding ratio requirements for certain large and complex banking organizations
- **Brokered Deposit and Interest Rate Risk Restrictions**
Less than well capitalized financial institutions
- **Interagency Policy Statement on Funding and Liquidity Risk Management on the Importance of Contingency Funding Plans**
Actionable contingency funding plans based on range of possible stress scenarios. Encouraged to incorporate the discount window as part of the contingency planning.



CONCLUSION

CECL Takeaways

- Forward looking
- Granularity
- Model selection

Liquidity Takeaways

- Early warning indicators
- Stress testing
- Contingency funding plans

Final Thoughts



QUESTIONS?

Q&A

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WILARY WINN LLC

A blue-tinted photograph of two men in business suits. The man on the left is leaning over the desk, pointing at a document. The man on the right is seated, wearing glasses and a beard, looking at the document with a smile. The background is a dark blue with a subtle geometric pattern.

Thank You

ADVICE TO STRENGTHEN FINANCIAL INSTITUTIONS



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