CECL

TOPICS FOR TODAY'S SESSION

- Accounting and Regulatory Context
- Loss rates are not linear
- Use of Data
- CECL Models
- WARM vs. DCF Comparison
- WW DCF Model
- Key CECL Takeaways
- Conclusion & Q&A

WILARY WINN

TODAY'S SPEAKERS

Douglas Winn

651-346-3517

dwinn@wilwinn.com

Michael Tessier

952-444-6646

mtessier@wilwinn.com

Accounting and Regulatory Context

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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

Applicability

CECL Applies to:

- Loans
- HTM Securities
- Net Investment in leases
- Off balance sheet credit exposures
- Loan commitments
- Standby letters of credit
- Financial guarantees/similar instruments

Major Provisions

- Departs from incurred loss model – probable threshold removed and CECL results in day one life of asset loss recognition
- Loss is recognized through an allowance for financial assets, including HTM debt securities, and through a liability for off balance sheet exposures
- Changes in the allowance – positive and negative are recorded immediately through credit loss expense

Measuring Credit Losses

- Net carrying amount should be based on the cash flows an entity expects to collect
- Contractual cash flows are adjusted for expected prepayments and defaults
    - Cash flows should not be adjusted for extensions, renewals, or modifications unless a TDR is reasonably expected
- Cash flows expected to be collected are discounted at the effective interest rate when using a discounted cash flow method
    - Credit loss is carrying amount less present value of expected cash flows
- Measure expected losses on a pool basis whenever similar risk characteristics exist

Estimating Expected Credit Losses

- Consider relevant information – internal and external

- Do not rely solely on past events – adjust historical loss information for:
  - Current asset specific risk characteristics
  - Current conditions
  - Reasonable and supportable forecasts

- Life of loan estimate – to estimate losses after reasonable forecast time period revert to historical loss rates

Regulatory Perspective

- Standard does not specify a single method for measuring expected credit losses
- Smaller and less complex institutions do not have to use costly and complex models
- Institutions may apply different modeling methods to different groups of financial assets

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.
- **Moss Adams guide to CECL**
- **AICPA CECL Practice Aid**: Offers audit considerations for CECL, focusing on internal controls, data reliability, model assumptions, and audit committee oversight.

Non-Linear Loss Rates

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Non-Linear Loss Rates

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	8.668%
1,250,000	**650**	**80%**	**2.338%**	**11.868%**	**38,028**	**3.042%**

Loan Amount	FICO	LTV	CDR	Severity	CECL Reserve ($)	CECL Reserve (%)
250,000	650	80%	0.704%	11.283%	2,767	1.107%
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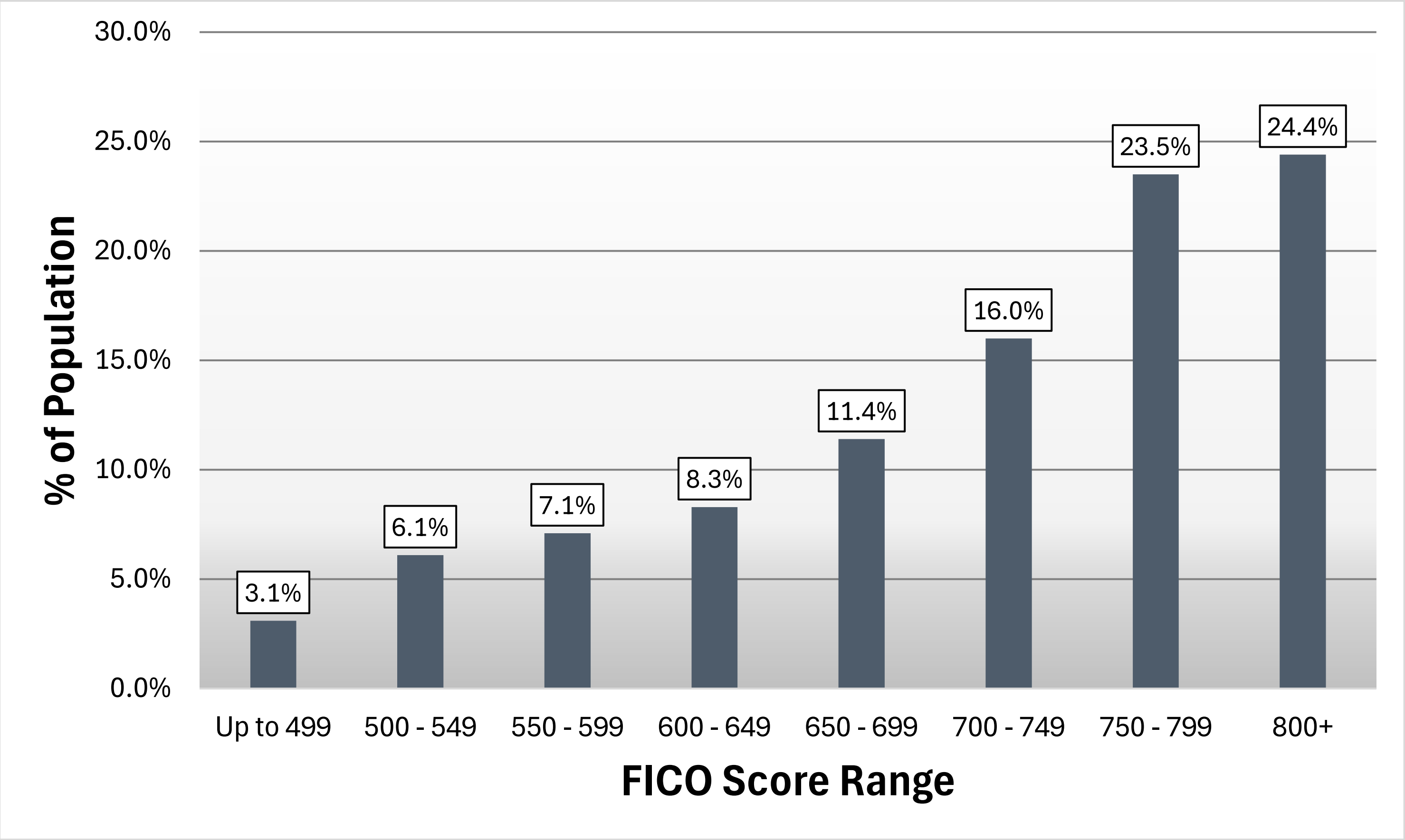
1,250,000	**650**	**80%**	**0.704%**	**11.283%**	**13,835**	**1.107%**

Non-Linear Loss Rates



Use of Data

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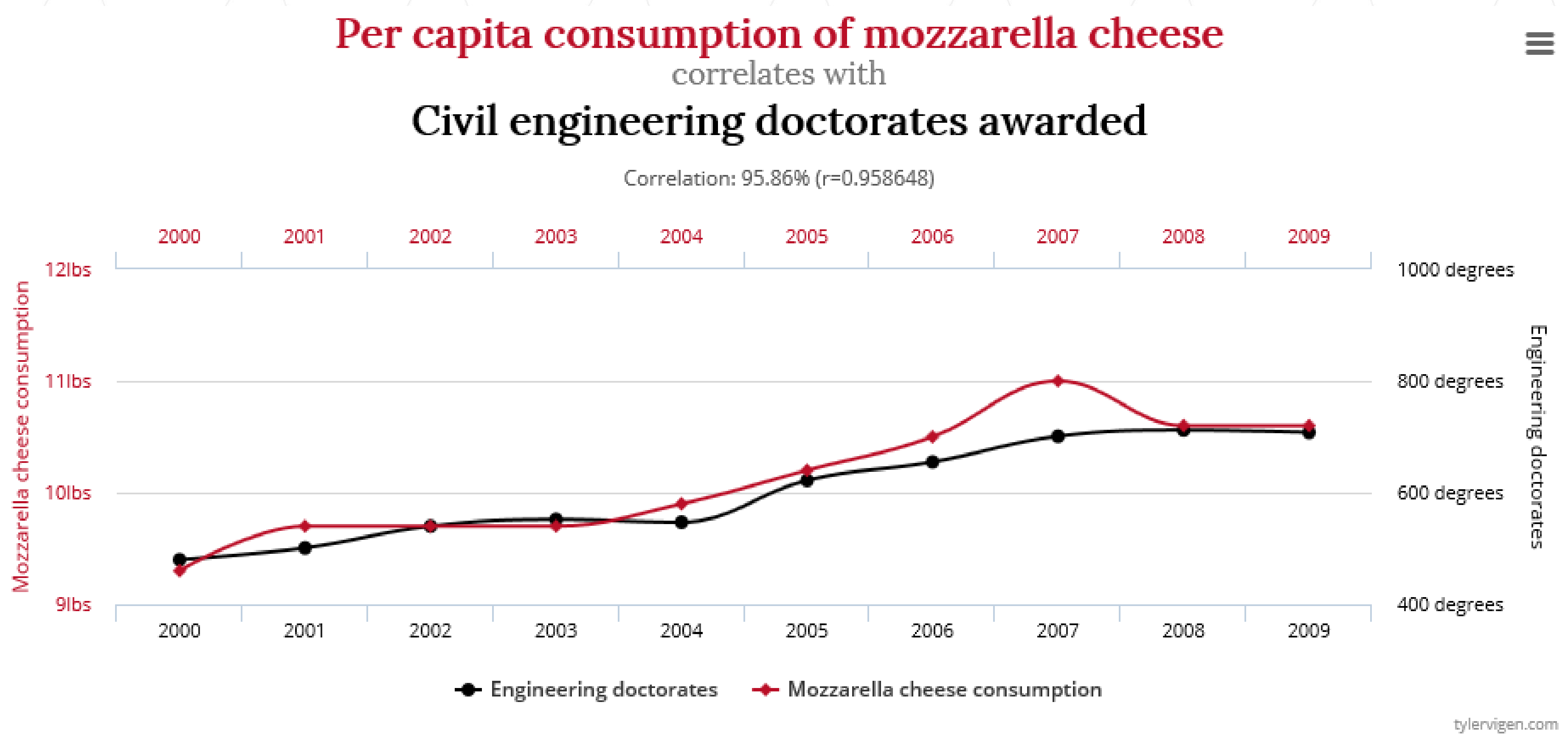
Data Considerations

- Predictive Inputs – Correlation is Not Causation
- Granularity
- Relevant lookback periods
- Use of industry data to supplement

Correlation is not Causation



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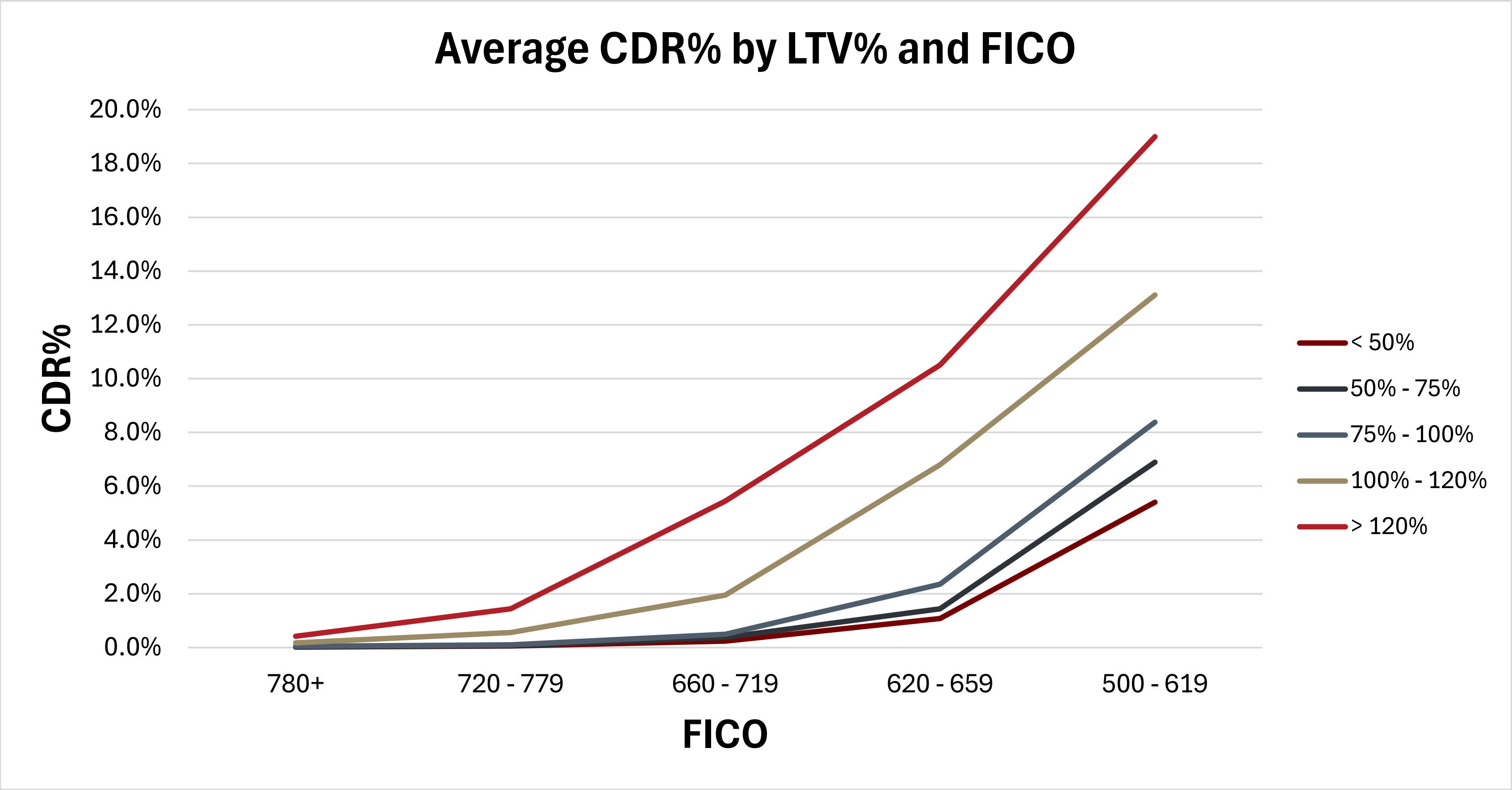
Predictive Credit Indicators

Examples– Performance of:

- Residential real estate loans is highly correlated to FICO **and** CLTV
- CRE is highly correlated to DSCR **and** LTV
- C & I loans is correlated to industry
- Auto loans is highly correlated to type of loan, FICO score loan term, and unemployment rate

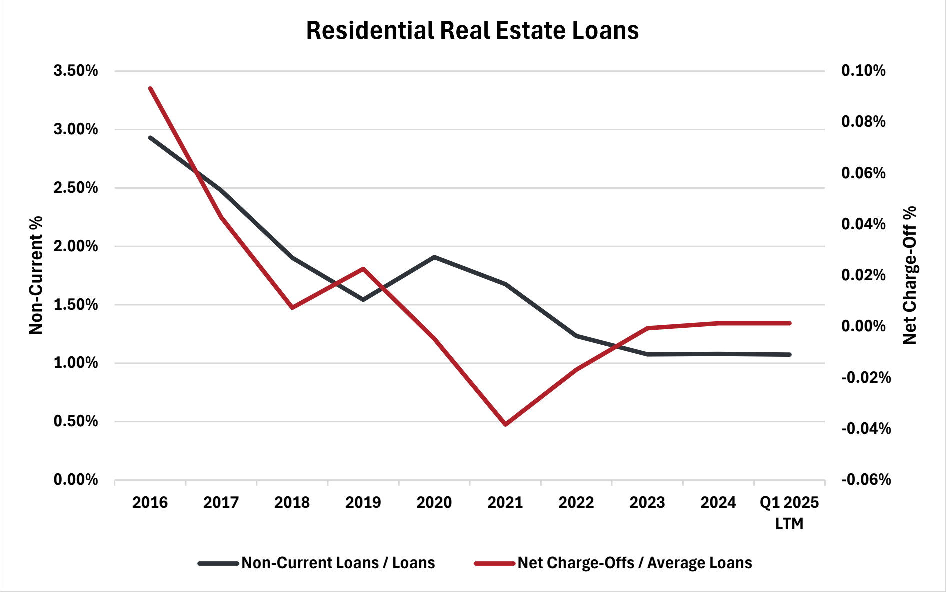
Predictive Inputs



Industry Insights by Loan Type

Residential Real Estate Loans

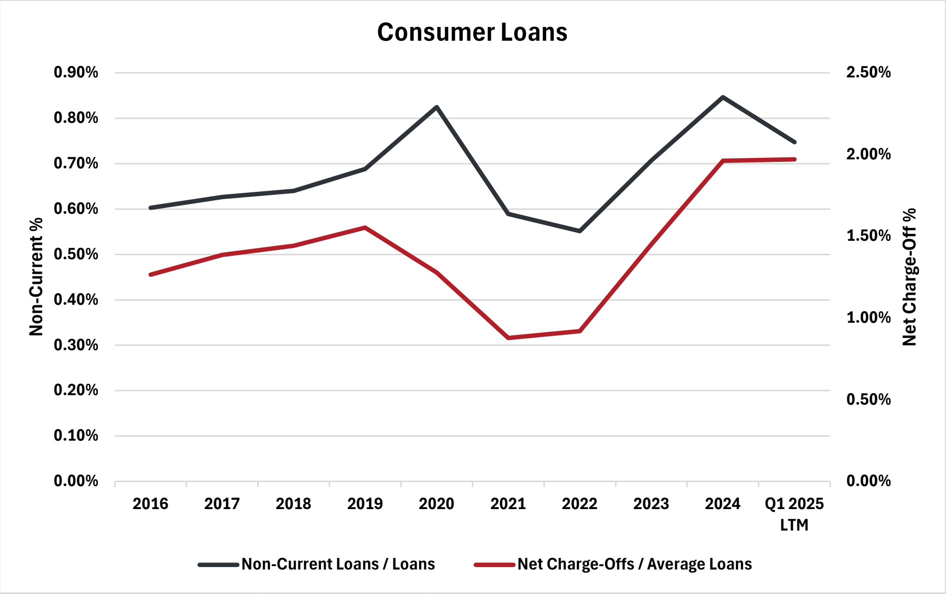
- **Housing Market Sensitivity**
- **Creditworthiness of Borrowers**:
    - Credit scores (FICO)
    - Loan-to-value ratios (LTV)
- **Prepayments**
- **Market Volatility**



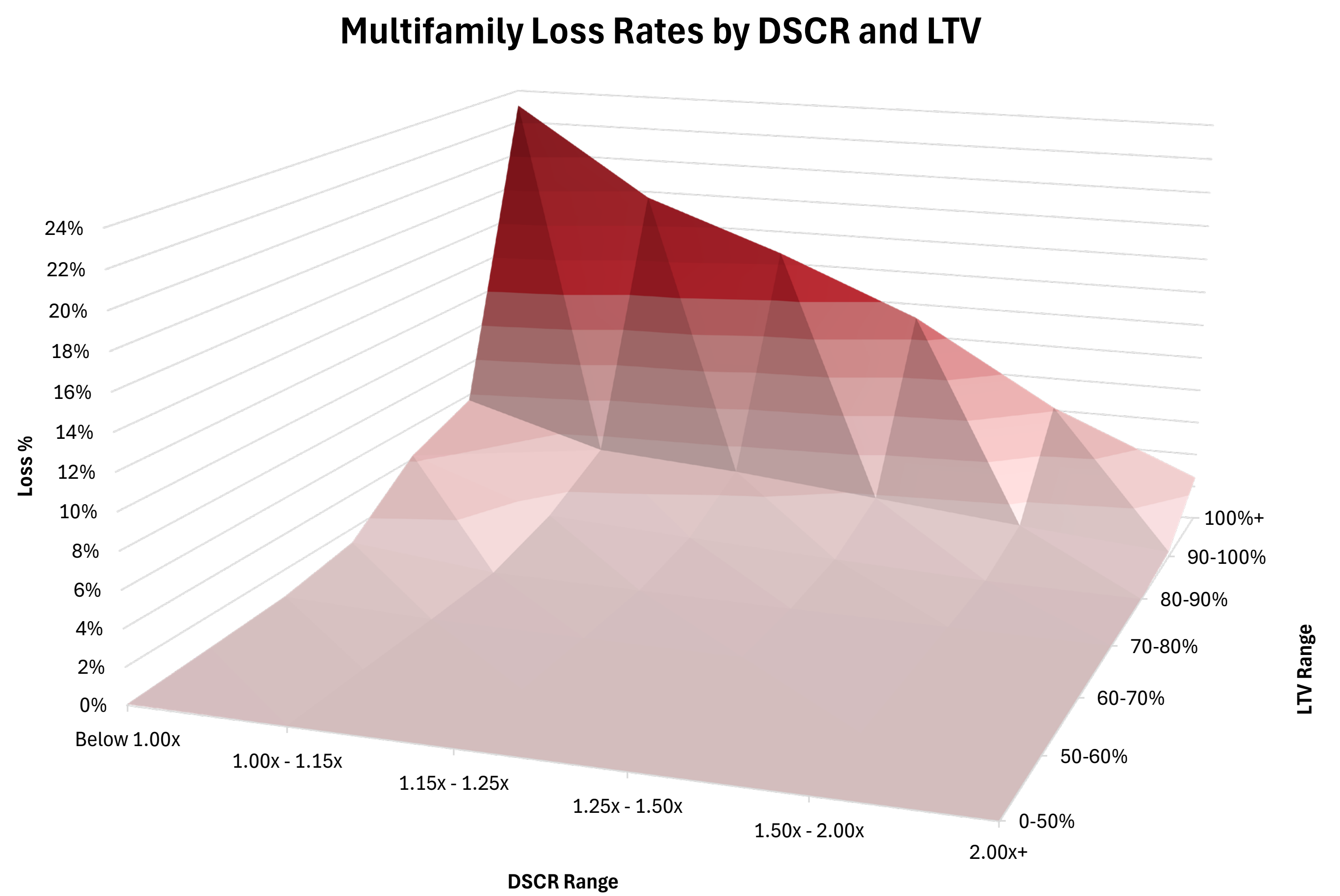
Industry Insights by Loan Type

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



CRE Loss Rates



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Loan Stratification – Cohort NAICs

SBA Charge-Off Rates by NAICS Code

NAICS Description	2007	2008	2009	2010	2011	2012
Bowling Centers	2.49	3.66	4.81	6.07	1.37	7.17
Car Washes	2.37	7.28	9.00	9.21	3.18	3.48
Gasoline Stations	2.57	4.14	6.55	7.55	3.83	4.04
Hotels and Motels	1.75	3.45	5.03	7.91	3.31	3.00
Machine Shops	1.22	3.59	4.09	3.29	2.03	1.32
Offices of Dentists	0.84	2.28	4.13	3.60	1.50	1.77
Offices of Lawyers	0.60	1.89	1.89	4.13	2.14	0.66
Veterinary Services	0.23	0.70	1.95	0.63	1.15	0.41

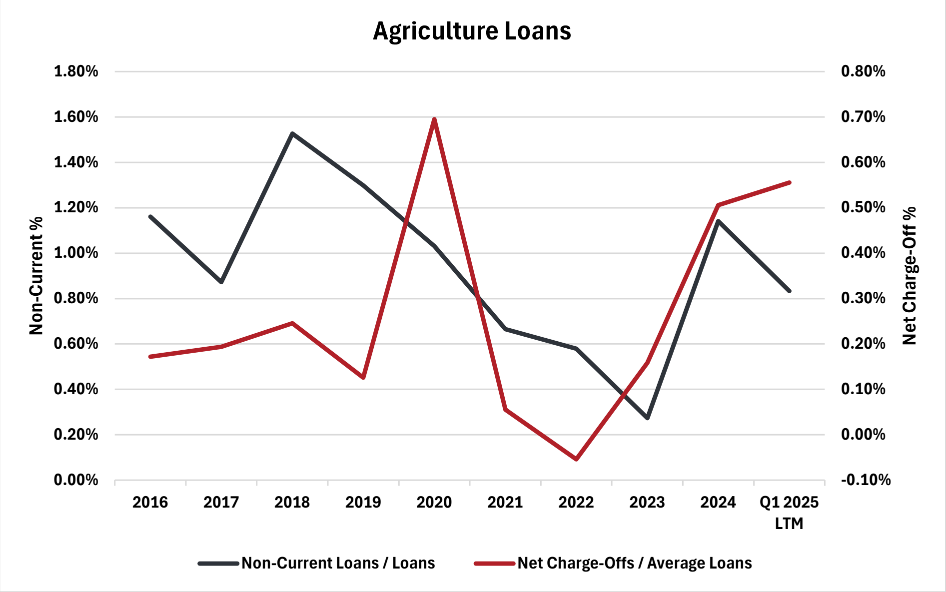
Industry Insights by Loan Type

Agricultural Loans

- **Unique Risk Profile**
  - Seasonal cash flow variability
  - Commodity prices
  - Weather conditions
  - Government policies

- **Collateral Valuation Challenges**

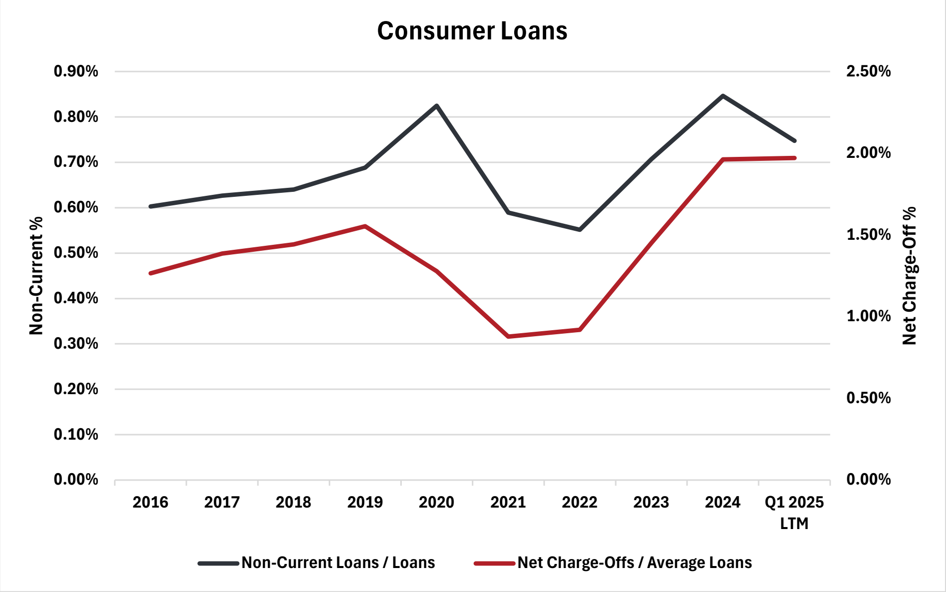
- **Geographic Sensitivity**



Industry Insights by Loan Type

Consumer Loans

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



Loan Stratification - Cohort

Collateral Type	FICO Cohort	CRR %	CDR %	Severity %	Future Loss %
New Vehicle - Direct	680 - 719	18.03%	0.28%	31.28%	0.17%
Used Vehicle - Direct	680 - 719	18.04%	0.64%	30.91%	0.35%
New Vehicle - Indirect	680 - 719	18.09%	0.44%	34.08%	0.32%
Used Vehicle - Indirect	680 - 719	17.90%	0.88%	33.82%	0.59%

Granularity

- The more granular the more predictive
- Statistically valid sample
- Creditability theory

Loan Stratification - Cohort

Collateral Type	CRR %	CDR %	Severity %
Used Vehicle - Direct Current 780+	17.91%	0.05%	29.30%
Used Vehicle - Direct Current 760-779	18.02%	0.14%	30.12%
Used Vehicle - Direct Current 720-759	18.12%	0.35%	29.96%
Used Vehicle - Direct Current 680-719	18.04%	0.64%	30.91%
Used Vehicle - Direct Current 640-679	17.34%	1.72%	31.88%
Used Vehicle - Direct Current 620-639	16.09%	2.99%	31.20%
Used Vehicle - Direct Current 500-619	13.05%	6.60%	31.82%
Used Vehicle - Direct Current under 500	7.47%	23.00%	29.13%
Used Vehicle - Direct Delinquent 30-59	4.00%	33.64%	30.24%
Used Vehicle - Direct Delinquent 60-89	4.00%	68.99%	35.47%
Used Vehicle - Direct Delinquent 90+ & F/C	4.00%	79.45%	37.02%

Predictive Credit Indicators

Industry Data Sources

- Ratings agencies – S&P Global, Moody’s, Fitch
- Credit reporting bureaus
- Bloomberg
- Regulation AB reporting
- SBA
- FNMA
- FHLMC
- WW Proprietary Dataset

Questions So Far?

CECL MODELS

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Modeling Techniques

- Permits allowance calculation to be based on methods which "implicitly" include the time value of money
    - DCF explicitly considers time value of money
    - Loss-rate, roll-rates, probability of default methods, and provision matrices implicitly consider discount

- Contemplates use of mean and not mode if using statistical modeling

- Should be based on financial institution's lending strategy, loan portfolio composition and concentration

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

Vintage	Origination Amount	Net Charge-Offs Year 1	Year 2	Year 3	Year 4	Year 5	Remaining Lifetime Net Charge-Offs (%)	Remaining 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

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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 = MEDIAN (D)*
Loss Given Default (LGD)	19.48%	*G = MEDIAN (E)*
Unadjusted 2024 ACL %	0.27%	*H = F x 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 x 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%**

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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.

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% plus 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 versus DCF

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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.

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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%**

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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 %				
Year	Beginning Reserve	Chargeoffs	Provision Expense	Ending Reserve
2009	0.14%	0.94%	2.80%	2.01%
2010	2.01%	0.95%	2.19%	3.25%
2011	3.25%	1.13%	2.25%	4.37%
2012	4.37%	0.76%	0.03%	3.65%
2013	3.65%	0.31%	1.23%	4.57%
2014	4.57%	0.11%	-1.98%	2.48%
2015	2.48%	0.04%	-1.49%	0.95%
2016	0.95%	0.00%	-0.63%	0.31%
2017	0.31%	0.01%	-0.18%	0.12%
2018	0.12%	0.04%	0.04%	0.12%
2019	0.12%	0.01%	0.01%	0.11%
2020	0.11%	0.01%	-0.01%	0.09%
2021	0.09%	0.00%	-0.03%	0.06%
2022	0.06%	0.00%	0.00%	0.05%

WARM Method $				
Year	Beginning Reserve	Chargeoffs	Provision Expense	Ending Reserve
2009	723,701	4,680,674	14,021,839	10,064,866
2010	10,064,866	4,737,628	10,930,094	16,257,333
2011	16,257,333	5,651,152	11,263,524	21,869,706
2012	21,869,706	3,783,483	160,951	18,247,174
2013	18,247,174	1,562,865	6,164,640	22,848,949
2014	22,848,949	534,196	(9,901,772)	12,412,981
2015	12,412,981	219,601	(7,455,887)	4,737,494
2016	4,737,494	6,074	(3,174,353)	1,557,067
2017	1,557,067	45,723	(919,582)	591,763
2018	591,763	216,773	214,570	589,560
2019	589,560	71,727	56,292	574,124
2020	574,124	64,983	(65,099)	444,042
2021	444,042	16,287	(144,376)	283,379
2022	283,379	23,542	(18,287)	241,550

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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	Provsion 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	

Questions So Far?

WW Proprietary Model

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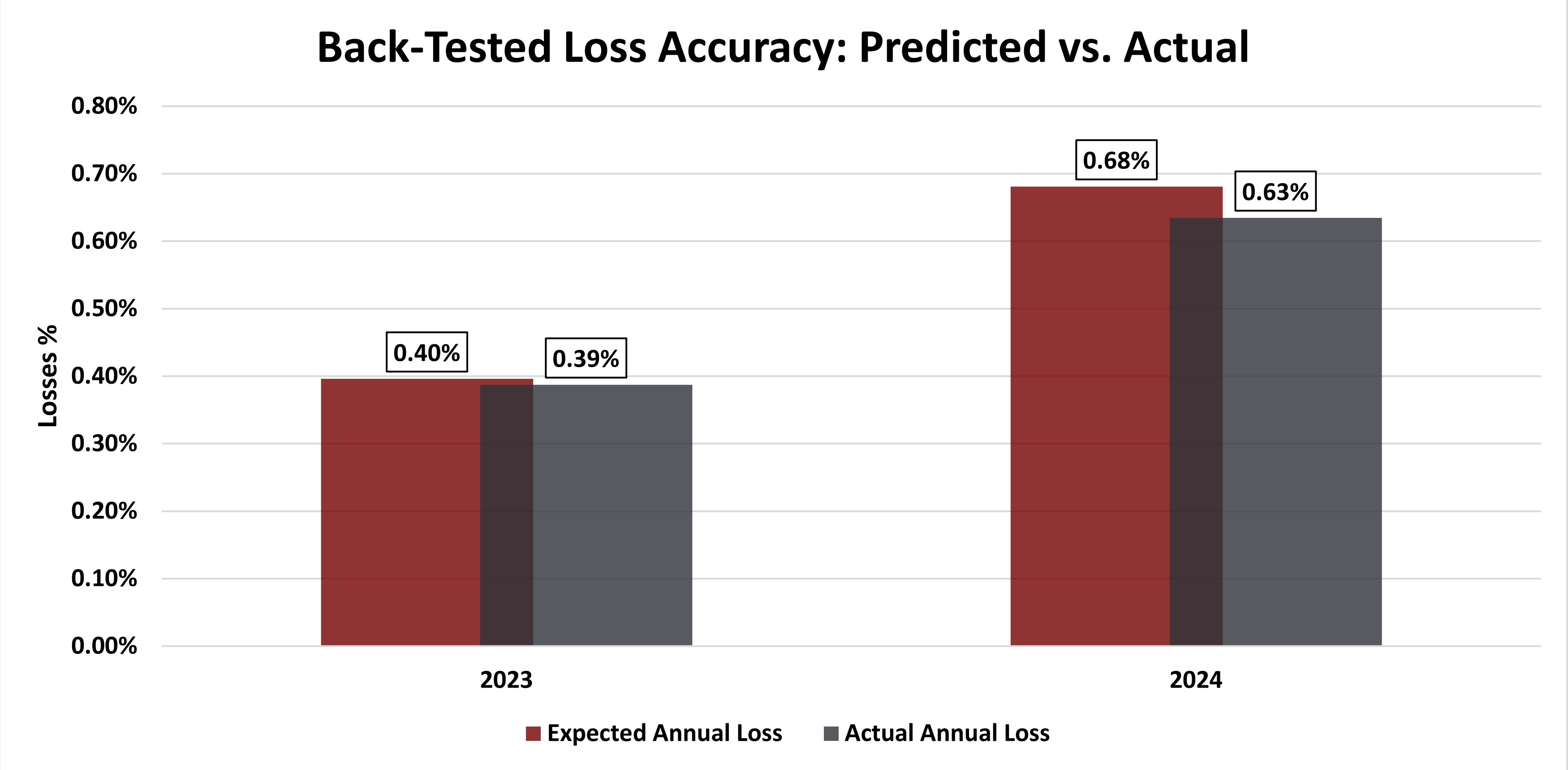
WW Proprietary Model Results



The results show that our models are highly predictive:

- For the year 2023, we predicted 0.40% of losses – actual net charge-offs were 0.39%.
- For the year 2024, we predicted 0.68% of losses – actual net charge-offs were 0.63%.

Discounted Cash Flow Analysis

It is very important to note that while we are applying our statistical inputs at the loan level in order to achieve a more accurate result for the aggregated cash flows, we do not for a moment believe our results are accurate for any given loan. In fact, we show a small percentage of each loan prepaying and defaulting each year – the latter, of course, being impossible. We are not re-underwriting individual loans, we are applying inputs – prepayment rates, default rates and loss given defaults, which we have derived from our statistical analysis to a pool of loans. Our results are intended to be accurate and to be used only in the aggregate.

Discounted Cash Flow Analysis

Key Valuation Inputs:

- Conditional Repayment Rate (CRR)
- Conditional Default Rate (CDR)
- Conditional Prepayment Rate (CPR = CRR + CDR)
- Loss Severity
- Discount Rate – depends on accounting context. For CECL it is original yield

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Deriving Initial Conditional Default Rates

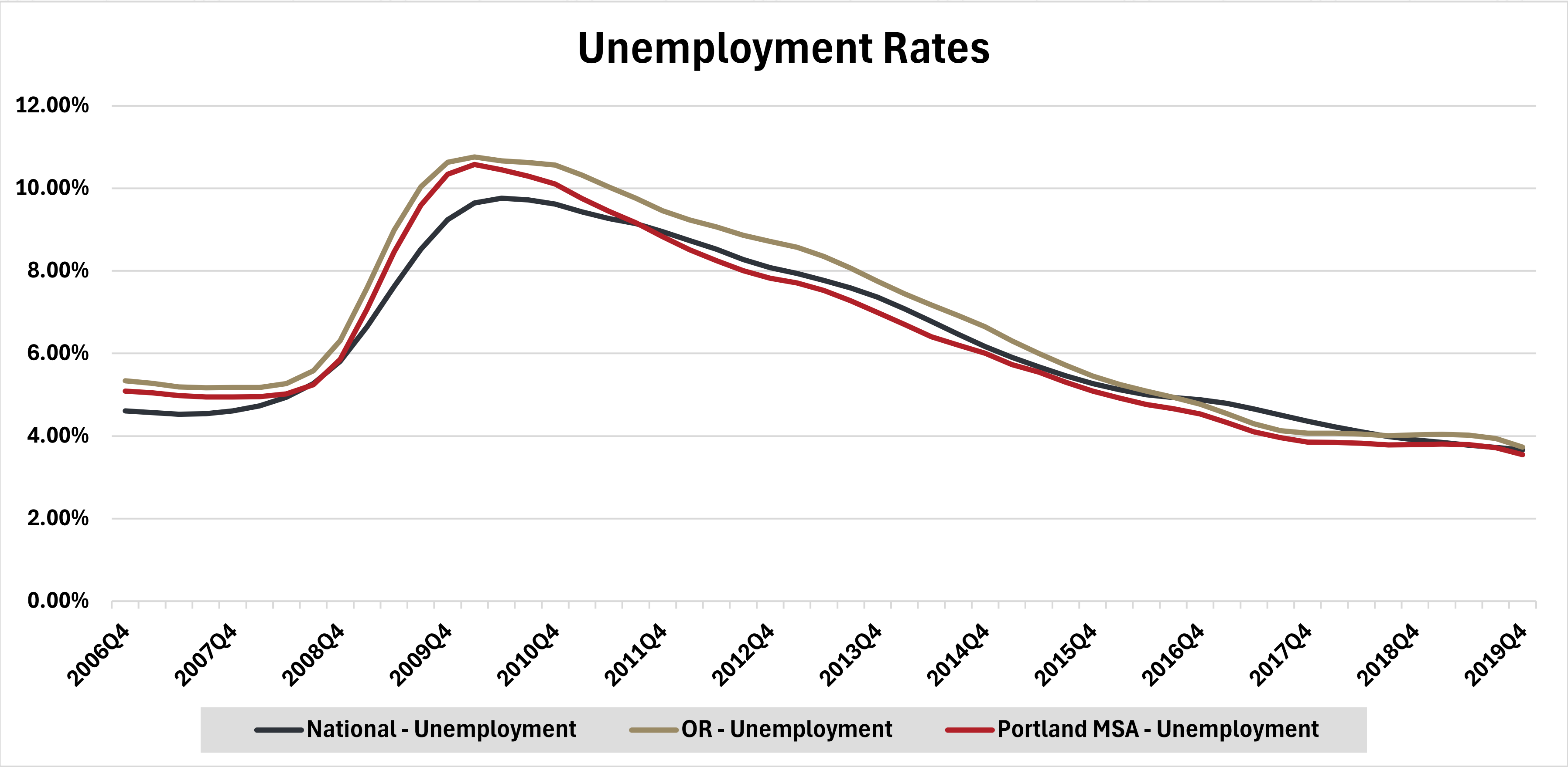
Data-Driven Default Assumptions by Loan Segment

Calibrated Using Historical Loan Performance and Borrower Risk Factors

- Initial CDRs are derived using a proprietary loan-level dataset spanning from 2008 through today, capturing full economic cycles.
- Based on individual loan characteristics including credit score, LTV/CLTV, term, loan type, and delinquency status.
- Assumptions applied at the loan-level based on these same characteristics.
- Historical performance trends inform segmentation logic, with higher CDRs assigned to loans exhibiting elevated risk (e.g., lower credit scores, higher LTVs, delinquency).
- Results are thus tailored to the characteristics of any given loan portfolio, adjusting dynamically as these attributes change.

Independent Variable

Predictive Inputs



Deriving Projected Conditional Default Rates

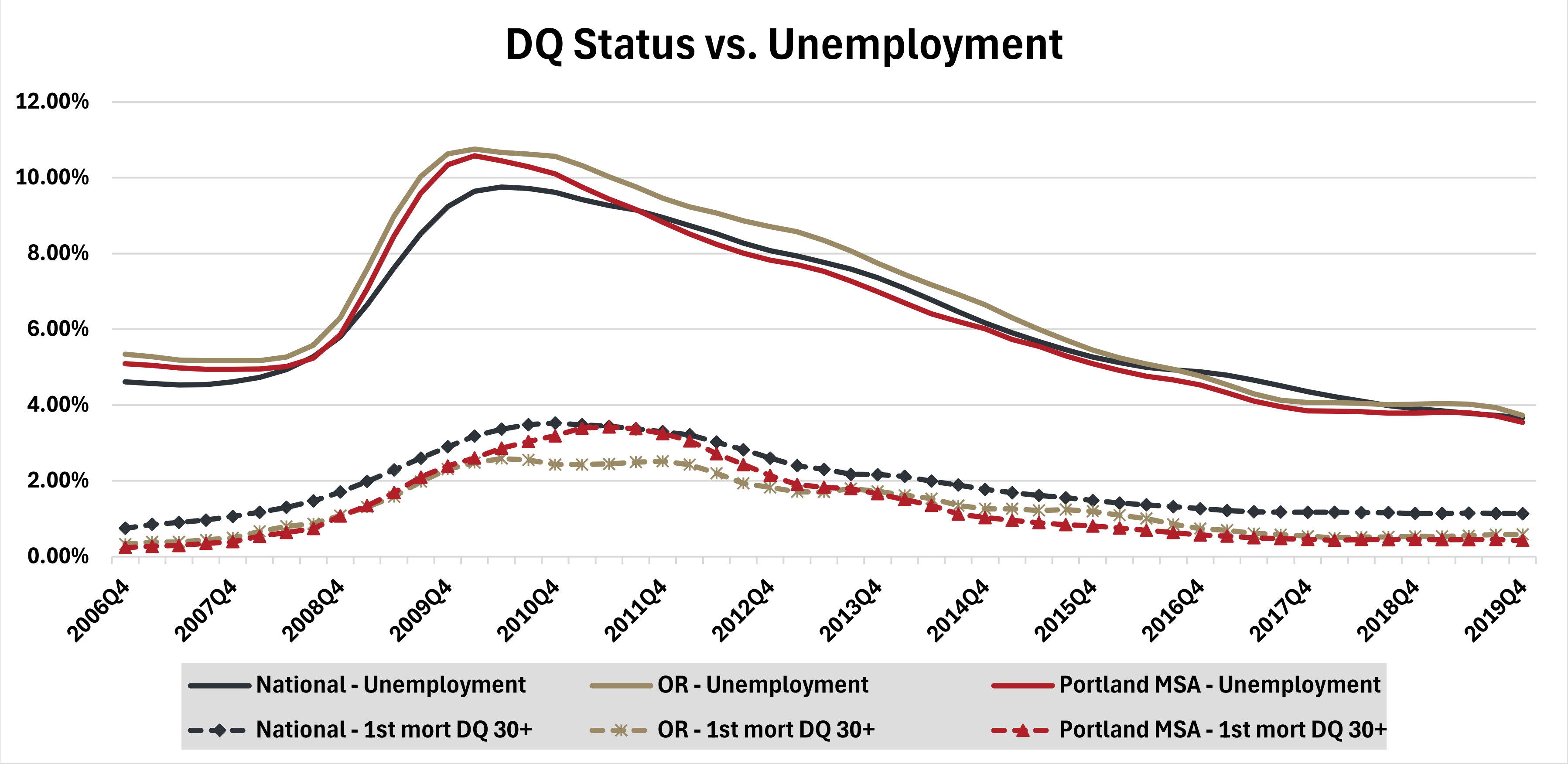
Predictive Inputs

Quantifying the relationship between unemployment and defaults:

- Perform regression analysis to determine best fit trend line including beta and R-squared
- Perform roll rate analysis to determine estimated default rates for any given unemployment rate
- Utilize changes between scenarios to determine default factors

Statistical Relationships

Predictive Inputs



Modeled Default Rates

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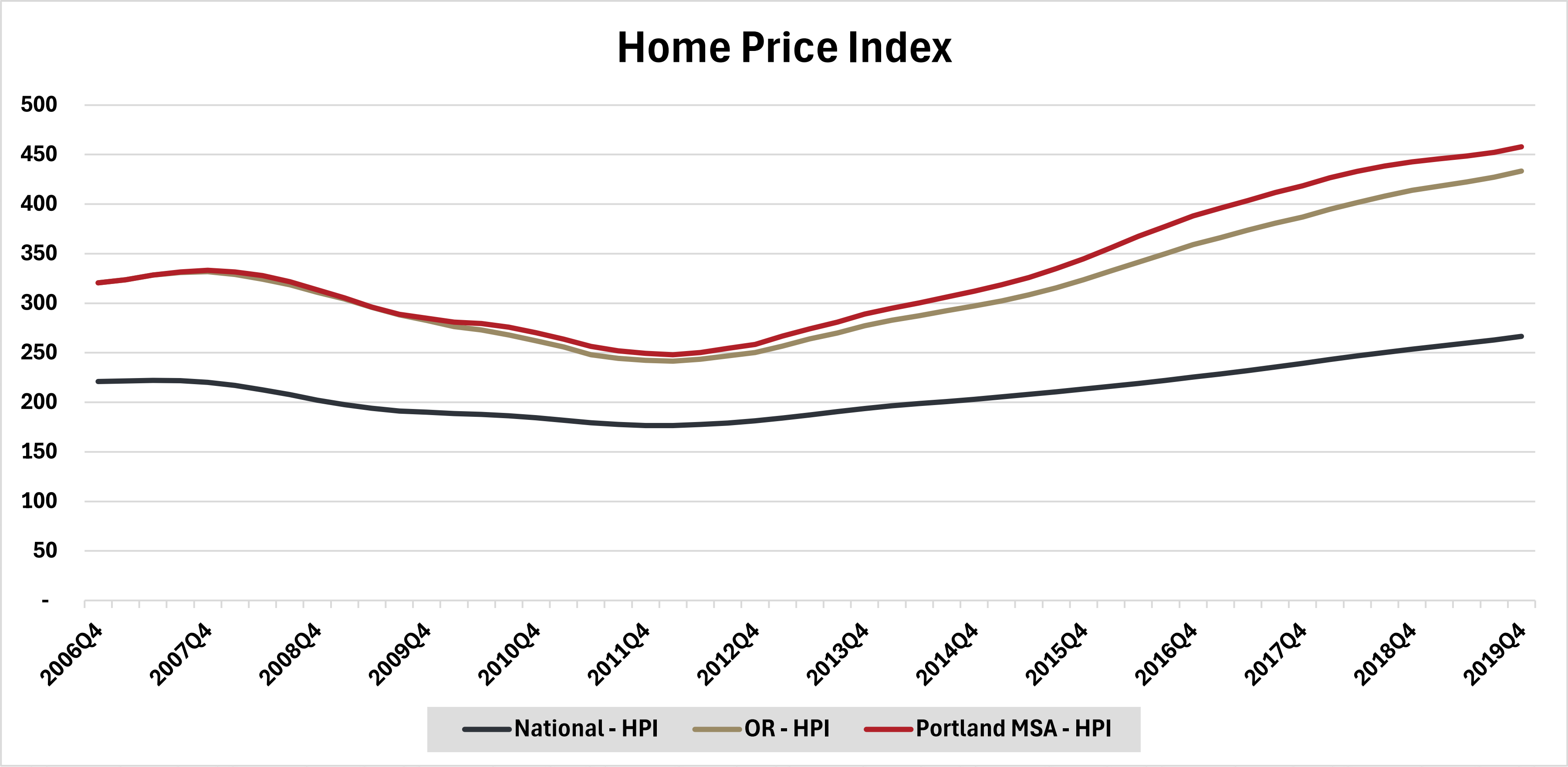
Predictive Inputs – Portland MSA

Unemployment and Default Factors by Year - Cyclical Assumptions											
		Yr. 1	Yr. 2	Yr. 3	Yr. 4	Yr. 5	Yr. 6	Yr. 7	Yr. 8	Yr. 9	Yr. 10
Market	Loan Category	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Unemployment											
National		4.35%	6.99%	9.91%	9.73%	8.97%	7.97%	6.96%	5.71%	4.98%	4.61%
Portland MSA		4.74%	9.16%	10.56%	10.27%	8.84%	7.75%	6.59%	5.54%	4.69%	3.84%
Estimated Default Factors											
Portland MSA	1st Mortgage - Fixed	108%	217%	337%	330%	298%	257%	215%	164%	133%	118%
Portland MSA	1st Mortgage - Adjust	109%	238%	381%	372%	335%	286%	236%	175%	140%	122%
Portland MSA	Other RE - Fixed	108%	219%	342%	334%	302%	260%	218%	165%	134%	119%
Portland MSA	Other RE - Adjust	102%	137%	176%	173%	163%	150%	137%	120%	111%	106%
Portland MSA	Credit Card	105%	138%	148%	146%	135%	127%	119%	111%	104%	100%
Portland MSA	Other Consumer	112%	194%	221%	215%	188%	168%	147%	127%	111%	100%
Estimated Default Rates											
Portland MSA	1st Mortgage - Fixed	0.27%	0.54%	0.84%	0.82%	0.74%	0.64%	0.54%	0.41%	0.33%	0.29%
Portland MSA	1st Mortgage - Adjust	0.18%	0.40%	0.64%	0.62%	0.56%	0.48%	0.39%	0.29%	0.23%	0.20%
Portland MSA	Other RE - Fixed	0.20%	0.40%	0.63%	0.62%	0.56%	0.48%	0.40%	0.31%	0.25%	0.22%
Portland MSA	Other RE - Adjust	0.27%	0.36%	0.46%	0.45%	0.43%	0.39%	0.36%	0.31%	0.29%	0.28%
Portland MSA	Credit Card	0.94%	1.24%	1.33%	1.31%	1.22%	1.14%	1.07%	1.00%	0.94%	0.90%
Portland MSA	Other Consumer	0.65%	1.13%	1.28%	1.25%	1.09%	0.97%	0.85%	0.74%	0.64%	0.58%

Collateral Value Considerations

Predictive Inputs



Modeled Appreciation/Depreciation

Predictive Inputs

HPI Impact by Year - Cyclical Assumptions											
	Yr. 0	Yr. 1 2026	Yr. 2 2027	Yr. 3 2028	Yr. 4 2029	Yr. 5 2030	Yr. 6 2031	Yr. 7 2032	Yr. 8 2033	Yr. 9 2034	Yr. 10 2035
Oregon											
Appreciation/(Depreciation)%		-12.1%	-8.6%	-9.0%	-1.2%	10.9%	8.3%	6.7%	11.8%	8.4%	8.5%
LTV%	90%	94%	103%	106%	118%	112%	98%	90%	81%	71%	63%
Severity%		31%	35%	34%	38%	31%	18%	15%	15%	15%	15%
CDR%		0.3%	0.6%	0.4%	0.3%	0.3%	0.2%	0.1%	0.1%	0.0%	0.0%
Losses%		0.0%	0.0%	0.1%	0.2%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%
Portland MSA											
Appreciation/(Depreciation)%		-12.5%	-5.2%	-9.2%	-2.3%	13.4%	8.3%	8.7%	13.8%	8.3%	8.1%
LTV%	90%	93%	103%	104%	114%	108%	94%	85%	76%	65%	59%
Severity%		30%	35%	32%	35%	28%	15%	15%	15%	15%	15%
CDR%		0.4%	1.1%	0.6%	0.3%	0.2%	0.2%	0.1%	0.1%	0.0%	0.0%
Losses%		0.0%	0.0%	0.2%	0.4%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%

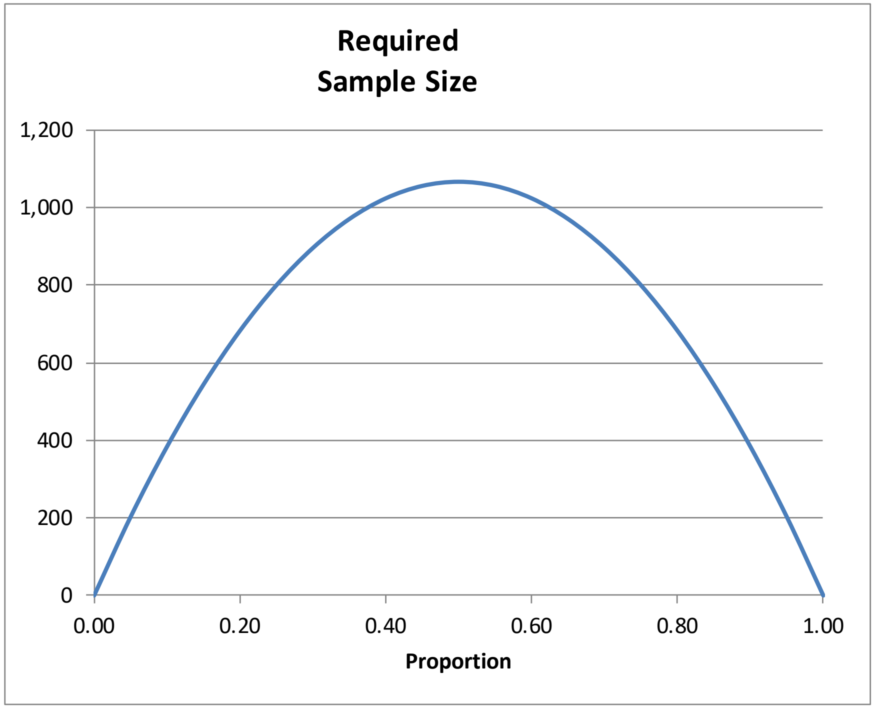
Discounted Cash Flow Analysis

Loan Type	Payment Status	Credit Score	LTV Status	LTV %	Ending Balance	Annual Prepay % (CRR)	Annual Default % (CDR)	Loss Severity %	Avg Life	Gross Future Losses	Discount Rate (WAC)	Discounted Future Losses	Discounted Lifetime Future Losses %	Discounted Annual Future Losses %
Fixed	Current	720+	Under 50%	45%	13,500,000	10.0%	0.0%	0%	7.0	-	4.0%	-	0.0%	0.0%
	Current	720+	50% - 75%	65%	9,450,000	9.0%	0.1%	0%	7.1	-	4.0%	-	0.0%	0.0%
	Current	720+	75% - 100%	85%	5,400,000	8.0%	0.1%	6%	7.6	2,416	4.0%	1,793	0.0%	0.0%
	Current	720+	100% - 120%	115%	3,150,000	7.0%	0.4%	30%	8.0	30,865	4.0%	22,510	0.7%	0.1%
	Current	720+	120% - 150%	140%	1,350,000	4.0%	1.3%	43%	9.5	71,685	4.0%	49,327	3.7%	0.4%
	Current	720+	Over 150%	175%	450,000	4.0%	1.8%	54%	9.0	39,790	4.0%	27,902	6.2%	0.7%
Repeat for FICO Buckets														
	Current	660-719	by LTV bucket	101%	6,525,000	6.0%	1.0%	20%	8.2	108,771	4.5%	75,927	1.2%	0.1%
	Current	620-659	by LTV bucket	70%	2,115,000	5.0%	3.5%	0%	8.0	-	5.0%	-	0.0%	0.0%
	Current	500-619	by LTV bucket	88%	1,350,000	4.0%	13.0%	9%	6.0	90,243	5.5%	65,452	4.8%	0.8%
	Current	Under 500	by LTV bucket	85%	1,462,500	4.0%	20.0%	6%	5.0	86,463	5.5%	66,066	4.5%	0.9%
	Delinquent	30-59 days		70%	45,000	4.0%	30.0%	0%	4.1	-	4.0%	-	0.0%	0.0%
	Delinquent	60-89 days		88%	135,000	2.0%	50.0%	9%	3.3	18,928	4.0%	16,649	12.3%	3.8%
	Delinquent	90+ days		85%	67,500	2.0%	75.0%	6%	2.7	7,994	4.0%	7,195	10.7%	4.0%
ARM	repeat all FICO & LTV buckets above			125%	30,000,000	8.0%	2.5%	36%	6.0	1,620,000	4.2%	1,269,286	4.2%	0.7%
Total Mortgages				95%	75,000,000	7.9%	2.1%	19%	6.8	2,077,155	4.2%	1,602,106	2.1%	0.3%

Statistical Significance and Creditability

Margin for Error (M)	3%
Confidence Level (1-α)	95%

Proportion	Required Sample Size
0.00	0
0.05	203
0.10	384
0.15	544
0.20	683
0.25	800
0.30	896
0.35	971
0.40	1,024
0.45	1,056
0.50	1,067
0.55	1,056
0.60	1,024
0.65	971
0.70	896
0.75	800
0.80	683
0.85	544
0.90	384
0.95	203
1.00	0



Source: Edward (Jed) Frees, Professor – Risk and Insurance, Hickman-Larson Chair of Actuarial Science, University of Wisconsin Madison

Statistical Significance and Creditability

Materiality Example

500,000,000	Asset Size
200,000,000	Fixed Rate Mortgages
250,000	Average Loan Size
800	Number of Loans in Portfolio
75,000	Materiality Threshold

FICO	Balance	Balance %	Number of Loans	Proportion / CDR%	Severity	Estimated Loss Amount	Materiality Threshold	Confidence Level (1-α)	Margin for Error as a Proportion (M/π)	Margin for Error (M)	Required Sample Size	Estimated # of defaulted loans
780+	99,397,279	49.70%	398	0.03%	23%	6,858	12,002	0.95	1.750	0.05%	4,180	1
720 - 779	63,208,279	31.60%	253	0.10%	23%	14,685	14,685	0.95	1.000	0.10%	3,799	4
660 - 719	24,670,661	12.34%	99	0.64%	23%	36,587	14,635	0.95	0.400	0.26%	3,700	24
620 - 659	5,852,054	2.93%	23	4.51%	23%	60,687	12,137	0.95	0.200	0.90%	2,034	92
500 - 619	6,541,771	3.27%	26	13.73%	23%	206,648	19,632	0.95	0.095	1.30%	2,673	367
under 500	329,957	0.16%	1	23.06%	23%	17,498	1,750	0.95	0.100	2.31%	1,282	296
	200,000,000	100.00%	800	0.75%	23%	342,964	74,841	0.95		0.16%	17,668	783

250,000	Estimated Average Balance
800	Estimated Count of Loans
17,668	Required Sample Size

Fail

75,000 Materiality Threshold

Pass

Credibility Theory

New Estimator = Z × Company Estimator + (1 − Z) × Prior (Industry) Estimator

K = n/(n+k) where for some quantity k and company sample size n

k = 4/(L^2 * Prior Estimator)

Here, "L" is the proportion desired (margin for error as a proportion or M/π per the previous slide).

Credibility Theory

620 to 659 FICO Band – Industry CDR is 4.51% and Credit Union's 3.20%

We want to be 95% confident our sample is within 45% of true default probability

k= 4/(L^2 * Prior Estimator) = 4/(0.45^2 * 0.0451) = 197.09.

Thus, the credibility factor Z = 23/(23 + 197.09) = 0.1045.

Our final CDR estimate for the 620 to 659 FICO band is equal to our company input (10.45% * 3.20%) + (1 – 10.45%) * 4.51% or 4.37%.

DCF Is Superior to Other Models

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.

DCF Is Superior to Other Models

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.

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

RESOURCES

WEBPAGE: **https://wilwinn.com/resources/**

CECL: https://wilwinn.com/resource-type/cecl/

CECL Resource Center: https://wilwinn.com/resources/cecl-resource-center/

CECL and Credit in Recession: https://wilwinn.com/resources/cecl-and-credit-in-recession/

CECL Models: WARM vs. DCF: https://wilwinn.com/resources/cecl-models-comparing-warm-to-dcf-white-paper/

Contact Information

For more information about our services, please contact us:

Valuation of Mortgage Servicing Rights, Mortgage Banking Derivatives, & Other Loan Servicing (Commercial, SBA 7(a), Vehicle, etc.):

Anneliese Ramin – aramin@wilwinn.com

Eric Nokken – enokken@wilwinn.com

Asset Liability Management (ALM), ALM Validations, Concentration Risk, & Capital Stress Testing:

Michael Tessier – mtessier@wilwinn.com

CECL and CECL Validations:

Michael Tessier – mtessier@wilwinn.com

Cole Schulte – cschulte@wilwinn.com

Mergers & Acquisitions and Goodwill Impairment Testing:

Cole Schulte– cschulte@wilwinn.com