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# A Component-Based Model for Non-Maturity Deposit Decay Incorporating Interest Rate and Credit Spread Sensitivity

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## Abstract

Non-maturity deposits (NMDs)—such as checking, savings, and money market accounts—are a vital funding source for banks. Their lack of contractual maturity and the option for depositors to withdraw at any time makes modeling their decay complex, especially under changing market and credit conditions. This paper presents a component-based modeling framework for NMD decay, separating account closure probability from the average balance growth rate (ABGR) for surviving accounts. The model explicitly captures the influence of interest rate spreads, credit spreads, and balance size on non-core balances, while stable core balances are modeled with a baseline growth rate. This approach aligns with recent academic and regulatory research, supporting both interest rate risk and liquidity risk management. An illustrative example demonstrates the model's structure and sensitivity to key variables.

**Keywords:** Non-maturity deposits, deposit decay, ALM, IRRBB, credit spread, interest rate risk, core deposits, stress testing.

## 1. Introduction

Non-maturity deposits (NMDs) are a cornerstone of bank funding, typically providing a stable and cost-effective alternative to wholesale funding sources. However, their stability is behavioral, not contractual—depositors can withdraw funds at any time, and balances often respond to changes in interest rates, credit conditions, and market sentiment. This optionality creates challenges for banks seeking to model deposit decay rates for asset-liability management (ALM), interest rate risk in the banking book (IRRBB), and liquidity planning (Benckert, 2023; Basel Committee on Banking Supervision, 2016).

The purpose of this paper is to introduce a pragmatic and practical component-based framework for deposit modeling—an area that has often been either too academically focused or too simplistic in practice. The proposed model is inspired by the familiar structure of Expected Credit Loss (ECL) modeling for loans, where probability of default and loss given default are modeled separately. By analogy, we split deposit decay into account closure probability and balance attrition among surviving accounts. This approach is intended to bridge the gap between theory and practice, illustrating how dynamic deposit behaviors can be incorporated in a way that is both robust and actionable for the banking industry.

Traditional approaches often rely on historical runoff rates or static pool analysis, which may not capture the full range of drivers affecting deposit stability or adequately reflect stress scenarios (Benckert, 2023; BTRM, 2024). Recent research and regulatory developments highlight the need for models that can dynamically incorporate both interest rate and credit conditions, as well as differentiate between core and non-core balances (Basel Committee on Banking Supervision, 2016; Pierobon, 2023).

## 2. Literature Review

**Traditional and Static Approaches:**
Early NMD models often used historical averages or single-pool studies to estimate decay rates and betas, correlating deposit balances and rates with market rates. While these methods are straightforward, they can mask the heterogeneity of depositor behavior and fail to account for regime changes or stress events (Benckert, 2023).

**Dynamic and Stochastic Models:**
Stochastic models, including those based on the Ornstein-Uhlenbeck process, allow for scenario analysis and stress testing of deposit outflows. These models can incorporate seasonality, market rate

paths, and simulate stressed conditions where no new deposits are made (Kalkbrener & Willing, 2004; Benckert, 2023; García et al., 2015).

**Core vs. Non-Core Segmentation:**
Modern practice distinguishes between stable "core" balances, which are less sensitive to rate and credit changes, and "non-core" or "surge" balances, which are more volatile and responsive to economic incentives. This segmentation is crucial for accurate IRR and liquidity risk measurement (Basel Committee on Banking Supervision, 2016; Chen, 2024).

**Interest Rate and Credit Spread Sensitivity:**
Empirical studies show that non-core balances are sensitive to both interest rate spreads (the difference between market rates and deposit rates) and credit spreads (such as single-A bank spreads over SOFR or CDS spreads), especially during market or idiosyncratic stress (Pierobon, 2023; Faust et al., 2011). These effects are modest in normal times but become pronounced during periods of stress, as depositors become more sensitive to a bank's perceived creditworthiness.

**Macroeconomic Factors:**
Macroeconomic variables such as changes in unemployment rates or GDP growth have also been shown to impact deposit behavior, especially during periods of systemic stress (Pennacchi, 2008; Xiang, 2023).

**Expert Judgment and Scenario Analysis:**
Given the limitations of historical data, especially for extreme events, expert judgment and scenario analysis remain essential for calibrating and validating NMD models, particularly for liquidity stress testing (Basel Committee on Banking Supervision, 2016; Chen, 2024).

# 3. Model Structure

The proposed model separates NMD decay into two primary components:

## 3.1 Account Closure Rate (CR)

The probability that an account closes in a given period is modeled as a function of account age, relationship depth, and macroeconomic conditions:

$$\text{Logit}(CR) = \beta_0 + \beta_1 \cdot \ln(\text{Age}) + \beta_2 \cdot \text{Relationship Depth} + \beta_3 \cdot \Delta\text{Unemployment}$$

where:

- Age is account age in months,

- Relationship Depth is a binary variable (1 for deep, 0 for shallow),
- ΔUnemployment is the annual change in the unemployment rate.

The closure rate is then:

$$CR = \frac{1}{1 + e^{-\text{Logit}(CR)}}$$

### 3.2 Average Balance Growth Rate (ABGR)

For accounts that remain open, ABGR is modeled as the sum of a core (stable) component and a non-core (incentive) component:

$$ABGR = (\gamma_0 \cdot \text{Stable Ratio}) + [\gamma_{IR} \cdot (\text{IR Spread}) + \gamma_{CS} \cdot (\text{Credit Spread})] \cdot \ln(\text{Avg Balance}) \cdot (1 - \text{Stable Ratio})$$

where:

- $\gamma_0$ is the baseline growth rate for core balances,
- Stable Ratio is the proportion of the average balance considered core,
- $\gamma_{IR}$ and $\gamma_{CS}$ are sensitivity coefficients for interest rate and credit spreads,
- IR Spread is the market rate minus deposit rate,
- Credit Spread is, for example, the single-A bank spread over SOFR,
- Avg Balance is the average account balance.

This structure allows the model to reflect differing sensitivities across account types and sizes, and to respond dynamically to both interest rate and credit spread changes (Pierobon, 2023; Faust et al., 2011).

The overall monthly decay rate is then:

$$D_{\text{monthly}} = 1 - [(1 - CR) \cdot (1 + ABGR)]$$

## 4. Model Implementation

**Segmentation:**
Accounts are segmented by product type, customer type, balance tier, and possibly insured status, as behavior differs across these dimensions (Basel Committee on Banking Supervision, 2016; BTRM, 2024).

**Calibration:**

- **CR Model:** Estimated using logistic regression on historical account closure data.
- **ABGR Model:** Calibrated using regression analysis on historical balance growth, with particular attention to periods of rate and credit spread volatility.
- **Stable Ratio:** Calibrated based on minimum observed balances, volatility analysis, or expert judgment.

**Constraints and Validation:**

- **Parameter Caps:** To prevent implausible results (e.g., negative decay or unrealistically long durations), caps may be placed on ABGR and decay rates.
- **Stress Testing:** Scenarios with widened credit spreads and sharp rate changes are used to test model sensitivity and ensure reasonableness.
- **Expert Judgment:** Especially for severe liquidity stress, overlays or regulatory runoff rates (e.g., LCR) may be used if historical data is insufficient (Basel Committee on Banking Supervision, 2016).

## 5. Illustrative Example

The following example is not calibrated on real data but rather uses expert judgment to illustrate plausible results for typical customer and product segments. The challenge in developing such a model often lies in calibrating each parameter, especially when historical data is limited. Thus, robust sensitivity testing and benchmarking are essential to support and maintain the use of these models across portfolios and segments.

**Example of Scenario Assumptions:**

- Market Rate: 4.00% (annualized) held flat
- Deposit Rate: Pass-through Beta Assumption x Market Rate
- Credit Spread: 0.50% (normal)
- Δunemployment: 0 (no macroeconomic shock)
- Deep Relationship: Yes = 1 (assumes impact is binary)

**Example Parameters by Customer and Product Type:**

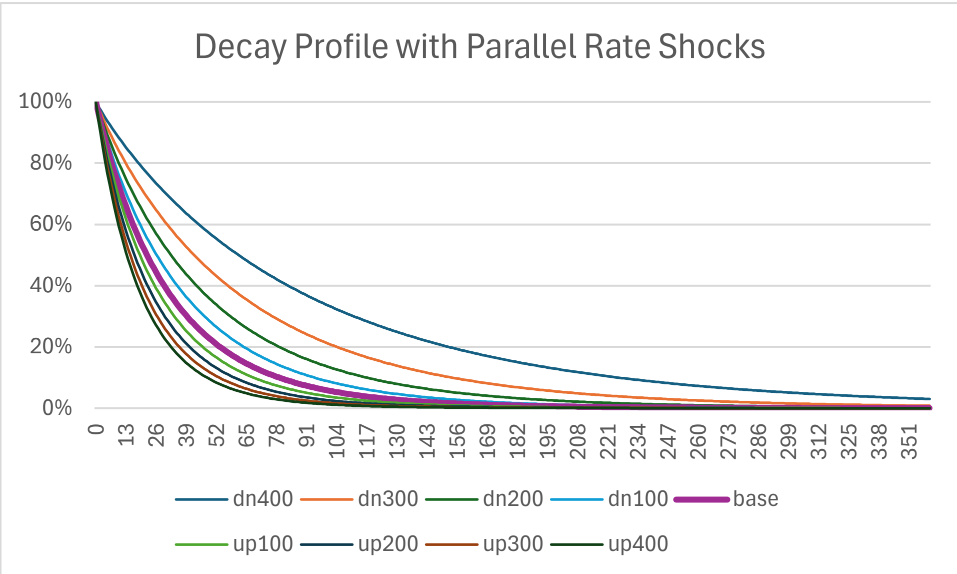
The following table are hypothetical parameters and coefficients assumed for 4 different customer and product segments. The Weighted Average Life (WAL) in years of each segment is calculated based on the assumed parameters. The parameters were not calibrated on actual data and were purely based on expert judgement for illustrative purposes.

| Customer Product Segment | Baseline Logit(CR) $\beta_0$ | log(age) $\beta_1$ | Relation-ship $\beta_2$ | ΔUnemploy-ment $\beta_3$ | Baseline ABGR $\gamma_0$ | Rate Spread $\gamma_1$ | Credit Spread $\gamma_2$ | Stable/ Core Ratio | Pass through Beta | Average Balance | WAL (yrs) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Retail_Checking | -3.00 | -0.15 | -2.00 | 1.00 | 0.10% | 12% | -8% | 80% | 0% | 10,000 | 6.88 |
| Retail_Savings | -4.00 | -0.15 | -1.00 | 1.00 | 0.10% | 12% | -10% | 40% | 50% | 50,000 | 3.97 |
| Commercial_Checking | -3.00 | -0.15 | -2.00 | 1.00 | 0.10% | 15% | -12% | 70% | 0% | 100,000 | 3.41 |
| Commercial_Savings | -4.00 | -0.15 | -1.00 | 1.00 | 0.10% | 20% | -15% | 25% | 75% | 500,000 | 2.86 |

**Example Calculations for Commercial Savings Segment (months 1-12):**

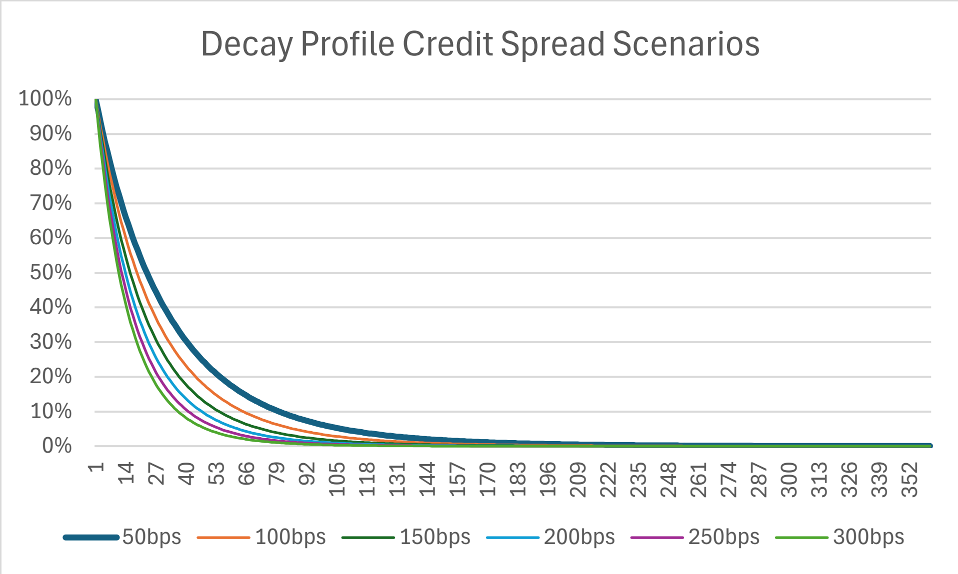
| Month | age | Relationship | ΔUER | Logit(CR) | Closure rate | Market Rate | Deposit Rate | Rate Spread | Credit Spread | Baseline ABGR | Stable Ratio | Average Bal | ABGR | Survival Rate | Decay Rate | Decay Profile |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | | | | | | | | | | | | | 100% | | 100% |
| 1 | 1 | 1 | 0 | -5.00 | 0.669% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $500,000 | -2.681% | 97% | 3.33% | 97% |
| 2 | 2 | 1 | 0 | -5.10 | 0.604% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $486,593 | -2.676% | 97% | 3.26% | 94% |
| 3 | 3 | 1 | 0 | -5.16 | 0.568% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $473,572 | -2.670% | 97% | 3.22% | 90% |
| 4 | 4 | 1 | 0 | -5.21 | 0.544% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $460,926 | -2.665% | 97% | 3.19% | 88% |
| 5 | 5 | 1 | 0 | -5.24 | 0.526% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $448,644 | -2.659% | 97% | 3.17% | 85% |
| 6 | 6 | 1 | 0 | -5.27 | 0.512% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $436,714 | -2.654% | 97% | 3.15% | 82% |
| 7 | 7 | 1 | 0 | -5.29 | 0.501% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $425,125 | -2.648% | 97% | 3.14% | 80% |
| 8 | 8 | 1 | 0 | -5.31 | 0.491% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $413,868 | -2.642% | 97% | 3.12% | 77% |
| 9 | 9 | 1 | 0 | -5.33 | 0.482% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $402,931 | -2.637% | 97% | 3.11% | 75% |
| 10 | 10 | 1 | 0 | -5.35 | 0.475% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $392,306 | -2.631% | 97% | 3.09% | 72% |
| 11 | 11 | 1 | 0 | -5.36 | 0.468% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $381,983 | -2.626% | 97% | 3.08% | 70% |
| 12 | 12 | 1 | 0 | -5.37 | 0.462% | 4.00% | 3.00% | -1.00% | 0.50% | 0.10% | 25% | $371,952 | -2.620% | 97% | 3.07% | 68% |

**Example Decay Profile for Commercial Savings Segment with Parallel Rate Shocks:**




| Scenario | dn400 | dn300 | dn200 | dn100 | base | up100 | up200 | up300 | up400 |
|---|---|---|---|---|---|---|---|---|---|
| WAL(Yrs) | 7.69 | 5.43 | 4.18 | 3.40 | 2.86 | 2.47 | 2.18 | 1.94 | 1.76 |

**Example Decay Profile for Commercial Savings Segment with Credit Spread Shocks:**




| Scenario | 50bps | 100bps | 150bps | 200bps | 250bps | 300bps |
|---|---|---|---|---|---|---|
| WAL(Yrs) | 2.86 | 2.31 | 1.94 | 1.68 | 1.47 | 1.31 |

## 6. Discussion and Implications

This component-based model allows for a nuanced understanding of NMD decay, supporting both IRRBB and liquidity risk management. By incorporating both interest rate and credit spread sensitivity, the model reflects empirical findings that non-core balances are especially vulnerable to both market and credit shocks. The segmentation of core and non-core balances, along with explicit modeling of closure and growth, aligns with best practices in recent literature and regulatory guidance (Basel Committee on Banking Supervision, 2016; Pierobon, 2023).

Adopting this component-based modeling approach allows a bank's ALCO and risk management teams to dynamically forecast deposit behaviors for both interest rate risk (IRR) and liquidity risk management within a unified, intuitive framework. By capturing customer sensitivity to economic incentives (rate spreads) and stress events (credit/liquidity spreads), the model enables:

- Strategic ALM, hedging, and liquidity planning by simulating deposit outflows under a range of interest rate and credit spread scenarios;
- Integrated IRR and liquidity stress testing, supporting both business-as-usual and adverse conditions with consistent modeling assumptions;
- Cohort- or account-level forecasting using a single, ECL-inspired structure that combines stable and non-stable balances, simplifying model governance and performance tracking;

- More robust scenario analysis, sensitivity testing, and benchmarking, which are essential for regulatory compliance and internal validation.

This pragmatic framework improves risk management by providing actionable insights for both IRR and liquidity, enabling banks to better align their funding, hedging, and contingency strategies with actual deposit behavior, and paving the way for more standardized and transparent deposit modeling industry-wide.

However, the challenge in developing such a model often lies in calibrating each parameter, especially when historical data is limited or absent for certain stress scenarios. Expert judgment is often required to ensure results are plausible across portfolios and segments, and robust sensitivity testing and benchmarking are essential to support and maintain the use of these models.

## 7. Conclusion

The purpose of this paper is to introduce a component-based framework for deposit modeling that is both pragmatic and familiar—mirroring the ECL approach for loans by splitting the modeling of closure risk and balance attrition. The proposed model illustrates how dynamic deposit behaviors, including responses to interest rate and credit spread changes, can be incorporated in a practical way. The illustrative examples are not calibrated to real data but are intended to demonstrate plausible outcomes for typical customer and product types. The framework is designed to help the banking industry improve its understanding of deposit behaviors and to better capture dynamic interest rate and liquidity stress scenarios.

The author encourages further research and invites practitioners to adapt this model, calibrate it on granular deposit data, and share their experiences and challenges with the broader community. Such collaboration will be essential for advancing the field and ensuring that deposit models remain robust and relevant as the financial landscape evolves.

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